Case Study of Road Weather Information Systems: Vehicle Sensor Integration for Accurate Winter Road Condition Estimation

by

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Abstract

The evaluation of winter road weather conditions poses a considerable difficulty for nations situated in high latitude areas, leading researchers to devise approaches aimed at enhancing the recognition of road conditions, enhancing travel safety, and minimizing winter road maintenance expenses. The successful combination of sensor data and advanced data processing techniques has been observed to effectively classify road conditions, specifically when using stationary Road Weather Information System (RWIS) stations. This approach is further enhanced by incorporating Geographic Information Systems (GIS) for interstation data interpolation. Consequently, a comprehensive framework is established for the continuous detection of winter road surface conditions. While the system generally proves effective, it faces limitations due to geographic constraints and the availability of RWIS stations. This thesis aims to explore potential solutions to address these challenges. The study proposes the use of dashcam images and the integration of On-Board Diagnostics II (OBDII) data to estimate winter road conditions. Additionally, it introduces a dynamic segmentation method to identify road segments with a high risk of hazards. To ensure the reliability of the findings, testing and validation are performed using real-world data from the Mobile Road Weather Information System (MRWIS) collected during the winter season of 2023. The culmination of this thesis involves performing a performance evaluation of our methodologies compared to the traditional stationary RWIS + GIS approach. This evaluation serves as a significant contribution to the advancement of winter road weather assessment. By overcoming existing limitations through the use of innovative technology and empirical analysis, our research has the potential to

greatly enhance the accuracy and effectiveness of evaluating winter road conditions. Ultimately, this can lead to safer travel especially in cold climate regions.

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Abbreviations

AASHTO American Association of State Highway and Transportation Officials.

AR Autoregressive model change.

CDA Cumulative Difference Approach.

CNNs Convolutional Neural Networks.

GIS Geographic Information Systems.

L1 Least absolute deviation.

L2 Least squared deviation.

MRWIS Mobile Road Weather Information System.

OBDII On-Board Diagnostics II.

PELT Pruned Exact Linear Time.

Rbf Radial basis function.

RGB Red Green Blue.

RKHS Reproducing Kernel Hilbert Space.

RSC Road Surface Condition.

RSI Road Surface Index.

RWIS Road Weather Information System.

SVM Support Vector Machine.

WRM Winter Road Maintenance.

Chapter 1

Introduction

1.1 Background

Canada and numerous other countries with harsh winters experience significant challenges due to dangerous road conditions during the cold months. According to the Federal Highway Administration, almost 21% of all traffic accidents in the United States are related to weather, often caused by the deterioration of the road surface conditions due to snow and ice accumulation. These hazardous conditions result in over 5,000 fatalities and 400,000 injuries annually [1]. Similarly, adverse winter weather, characterized by snow, ice, and reduced visibility, substantially increases the number of accidents, leads to frequent road closures, and disrupts traffic flow. The economic impact is also profound. Road traffic accidents cost the global economy an estimated $1.8 trillion in societal, hospitalization, and labor loss costs between 2015 and 2030 [2].

In response to these challenges, governments in regions with severe winters are compelled to allocate substantial resources to winter road maintenance programs. Abohassan [3] emphasizes that the use of anti-icing agents and mechanical snow removal is crucial for ensuring road safety and minimizing traffic disruptions during the winter months. However, such investments lead to substantial maintenance costs. To reduce these costs, efficient and accurate estimation of winter road conditions is essential for optimizing resource allocation and enabling transportation authorities to proactively manage road maintenance. However, current traditional methods for estimating road conditions have significant limitations.

One significant limitation is that existing Road Weather Information Systems (RWIS) and Geographic Information System (GIS)-based techniques often fall short in accurately detecting road conditions between two stations. Additionally, Regional and remote roads may not have adequate coverage of RWIS stations, making it more difficult to estimate real-time road conditions. Consequently, road condition estimates can be inaccurate or incomplete, leading to potential safety risks for drivers in these areas.

1.2 Problem Statement and Research Motivation

This research is motivated by the need to improve road condition estimation methods during the winter months, where traditional methods often fail to provide accurate and real-time data, especially under adverse weather conditions. The primary goal of this study is to develop a novel winter road condition estimation model that integrates data from onboard cameras and OBDII sensors. This integration aims to leverage real-time data on road surface conditions and vehicle dynamics to provide a comprehensive and accurate assessment of winter road safety.

The proposed model uses advanced technologies available in modern vehicles, such as onboard sensors and cameras, to capture detailed and real-time information about road conditions. By synthesizing data from these technologies, the model seeks to overcome the limitations of conventional techniques, thus enhancing the accuracy and reliability of the road condition assessments.

To verify the effectiveness of the model, extensive testing will be conducted across various winter weather scenarios using both historical and real-time data. These tests will cover a broad spectrum of conditions, including different types of snow, ice, and temperatures, with the aim of rigorously evaluating the accuracy of the model and its ability to function in diverse and challenging weather conditions.

Furthermore, the reliability and performance of the model will be validated using data from the Mobile Road Weather Information System (MRWIS), which provides localized, real-time weather and road condition information collected during maintenance operations. This validation seeks to confirm the model's adaptability and effectiveness in real-world conditions.

1.3 Objectives

As identified in previous sections, solely relying on stationary RWIS to predict winter road conditions has proven unreliable. In response to this limitation, this study proposes an approach that uses vehicles as sensors, incorporating various sensors such as cameras and OBD, to enhance the accuracy of winter road condition predictions. The incorporation of dynamic segmentation methods serves to enhance the accuracy for predictions across the entire highway corridor.

Placing this research in the context of existing literature requires a thorough investigation of the challenges related to precise road surface condition estimation, particularly to optimizing real-time winter road maintenance operations. The complexities of this research stem from the integration of diverse elements, including the selection of specific weather condition parameters, road surface images captured by vehicle dashcams, and the application of deep-learning and machine-learning models and strategic approaches. This combination reveals a level of interdependence and complexity that previous studies have not thoroughly explored.

In light of these considerations, the primary objective of this thesis is to develop a robust road condition classification model that integrates data from various vehicle sensors and dynamic segmentation methods for practical use in real-life winter road maintenance. The research unfolds in two distinct phases, each addressing specific aspects of the overarching objective. In phase one, the emphasis is on constructing a classification model as well as a dynamic segmentation method that outputs real-time, spatially continuous road condition estimates using data from vehicle sensors.

Phase two shifts the focus towards comparing model and method performance, the elements that can influence the final results.

To systematically achieve these overarching goals, the research is structured around the following specific tasks.

1. Develop a road condition classification method that incorporates data from various vehicle sensors and applies it in practice to obtain continuous, spatially continuous real-time road condition estimates.

2. Conduct a comparative analysis of widely adopted machine learning algorithms with the aim of identifying the most suitable algorithm for the precise classification of road conditions.

3. Investigate and compare existing dynamic segmentation methods, seeking to identify the optimal approach tailored to our specific testing conditions.

4. Generate a road condition map by the selected dynamic segmentation method. This map serves the dual purpose of helping Winter Road Maintenance (WRM) personnel make timely and effective decisions while providing crucial information to road users.

Through the systematic pursuit of these goals, this thesis aims to deliver a method for classifying continuous road conditions that is both accurate and intuitive. By contributing practical insights, the research endeavors to improve decision-making in WRM, ultimately enhancing safety and facilitating efficient resource allocation.

1.4 Thesis Outline

The remainder of this thesis is organized as follows:

Chapter 1: Introduction

This chapter introduces the challenges and impacts of winter road conditions on safety and traffic management. It outlines the motivation behind improving road condition estimation methods and discusses the specific objectives of this thesis.

Chapter 2: Literature Review

This chapter reviews the existing methods for detecting and estimating road surface weather conditions. It discusses various approaches, including the use of RWIS, machine learning techniques, and the integration of vehicle sensor data. The chapter also identifies gaps in current research and highlights the need for accurate real-time estimation methods that can adapt to diverse and changing winter conditions.

Chapter 3: Methodology

This chapter describes the methodologies used in this research, including the development of the algorithms for road condition estimation and dynamic segmentation. It details the integration of various data sources, such as camera feeds, OBDII, and RWIS data. The chapter also explains the data collection process, the experimental setup, and the methods used for data analysis and model validation.

Chapter 4: Case Study

This chapter presents a case study to validate the effectiveness of the proposed methods. It details the data collection on Highway 2 south of Edmonton, the data pre-processing steps, and the application of the developed models to estimate road conditions. This chapter evaluates the model's performance using real-world data and discusses the implications of the findings in the context of road safety and maintenance.

Chapter 5: Conclusions, recommendations and Future Work

The final chapter summarizes the findings of the research, revisiting the main objectives and discussing how the study contributes to the field of transportation engineering and road safety. It provides recommendations for future research and potential improvements in winter road condition estimation techniques. This chapter concludes with reflections on the impact of integrating advanced data processing techniques and real-time data for enhancing road safety during winter.

Following this structured approach, this thesis aims to contribute valuable insights to the field of road safety and transportation, fostering advancements in winter road condition estimation methods for safer and more efficient driving conditions during winter weather. The proposed winter road condition estimation model seeks to fill the gaps left by traditional methods, particularly in regional and remote areas, ultimately leading to improved road safety and resource optimization during harsh winter conditions. Additionally, by collecting and utilizing our own winter road condition data, this research not only enhances the accuracy and relevance of the model but also establishes a foundation for expanding the dataset in the future, further contributing to the robustness and applicability of winter road safety solutions.

Chapter 2

LITERATURE REVIEW

2.1 Methods for Road Surface Weather Condition Detection and Estimation

Throughout the years, extensive research has been carried out to detect and estimate the winter weather conditions on road surfaces. In general, these studies can be classified into three main types, each focused on the main difficulties encountered by winter maintenance agencies. These problems include the need to efficiently handle snow and ice management in the face of growing traffic, increasing public demands, and limited financial resources and personnel [4]. In recent years, there has been a increase in research dedicated to delivering dependable and uninterrupted data on the status of road surfaces. This research may be classified into three distinct types.

The first category of methods in this research area involves the processing and analysis of data collected from stationary stations, such as RWIS, weather base stations, and mobile RWIS, supplemented by remote sensing data. This approach aims to infer the state of the road surface across entire corridors or areas closely associated with these data sources. Gu [5] has done a thorough study on the surface temperatures of the corridor roads, relying only on data from RWIS stations. Similarly, Wu [6] utilized cameras mounted on RWIS stations to estimate road conditions near these locations.

However, despite the use of these methodologies, the field faces significant constraints. The high costs associated with the deployment and maintenance of RWIS and weather stations lead to their sparse distribution, creating considerable gaps between stations and consequently, inconsistencies in data quality and availability. Gu's study initially demonstrated the potential for precise prediction of road surface temperature, offering the possibility of accurately predicting winter road conditions. However, while Gu successfully predicted road surface temperature, the effectiveness of models based on MRWIS and the creation of semivariograms tends to decrease over time. Additionally, when attempting to use the predicted road surface temperature to forecast winter road conditions, significant discrepancies were found compared to the actual values obtained from MRWIS, indicating inherent limitations in the accuracy of such forecasts.

The second category of research use various of sensors and vehicle dynamics data to quantify road surface friction for categorization purposes. According to Khaleghian's summary [7], previous work on estimating road surface friction may be categorized into two main approaches: experiment-based and model-based. The former employs sensor data, such as sound and temperature sensors, and establishes correlations with characteristics linked to friction. The latter use simpler mathematical models to simulate the vehicle dynamic thus estimate the current road friction, which are categorized into dynamic wheel and vehicle methods, slip-based methods, and tire model-based methods. The vehicle dynamics-based approach may attain exceptional precision and consistency, however, the need for specialized equipment makes data collecting costly and arduous.

The third category encompasses the use of machine learning and deep learning, in conjunction with both visual and tabular data, for the purpose of predicting road conditions. Due to the emergence of deep learning, an increasing number of research projects have used machine learning and deep learning techniques to identify the state of winter roads. In 2010, Fu [8] demonstrated the practicality of using inexpensive cameras installed on standard automobiles together with Support Vector Machine

(SVM) to evaluate the state of road surfaces. Subsequent research further developed this method using sophisticated deep learning models that were trained with transfer learning techniques for the purpose of classifying dashcam images [9]. However, the precision of this approach may be influenced by environmental volatility. In order to improve the precision of winter road surface classification, a recent study conducted by Juan [10] has shown that integrating weather data (tabular data) with vision-based data obtained from dash cams can improve the accuracy and reliability of road surface condition classification. This advancement makes it possible to achieve a highly accurate and cost-effective detection of winter road conditions. Similarly, drawing parallels from the medical field, Gessert et al. [11] demonstrated a successful application of combining tabular data with visual data for enhanced classification. In their study for the ISIC 2019 Skin Lesion Classification Challenge, they implemented an advanced CNN architecture that integrates patient metadata with dermoscopic images to effectively address challenges such as severe class imbalances and varying image resolutions. Their method, which employs multiple model inputs and a dense neural network branch for tabular data, suggests potential strategies for refining the accuracy and robustness of road condition monitoring systems by incorporating analogous multimodal data integration techniques.

2.2 Factors Affecting the Detection of Road Surface Weather Conditions

Accurately identifying indicators for winter road conditions is crucial for classification and forecast purposes. The complexity of road conditions arises from the interplay of several factors, including weather, geography, and human activities, making its direct assessment challenging. Previous research, shown by the study by Pan et al. [9], has shown that certain environmental attributes, when evaluated with visual data, might improve the overall efficacy of models. Therefore, it is essential to identify weather attributes that improve performance.

2.2.1 Weather Conditions

Previous studies have shown a significant correlation between the winter road surface temperature and the accumulation of snow on the roads. The road surface temperature is influenced by several intrinsic factors, including solar radiation, wind velocity, humidity, altitude, latitude, elevation, and land use [12].

Ambient Temperature

The correlation between air temperature and road surface temperature is a crucial element in understanding winter road conditions. Gustavsson's research [13] highlights the correlation, especially on nights. His study demonstrates that the presence of nearby windbreaks has a substantial influence on air temperature fluctuations, thus influencing the temperatures of road surfaces. These results emphasize the need to take into account local meteorological variables, particularly variations in air temperature driven by wind and topographical characteristics, when estimating road surface temperatures. These findings are crucial for the development of precise road weather models and forecasting systems, which improve the safety and effectiveness of winter road maintenance.

Humidity

Sarsembayeva[14] investigated the influence of humidity on winter road surface conditions. This research highlights the crucial impact of humidity on the winter road surface temperatures. The study examines the impact of humidity fluctuations on the development of ice and frost on roads, a crucial factor in ensuring road safety and maintenance. The study focuses on the interplay between humidity and road temperature, specifically concentrating on water vapor migration and its influence on the road's structural qualities. Gaining a comprehensive understanding of this correlation is crucial for the advancement of road weather models, allowing improved forecasting and maintenance approaches for winter road conditions.

Wind Speed

Wind speed plays a significant role in modulating the temperature of both the air and the road surface by affecting the mixing of air layers and the dissipation of cold air pools[15]. Higher wind speeds enhance the mixing of cooler air near the surface with warmer air above, thus reducing the extremity of temperature gradients that develop under calm conditions. This process is particularly important in enclosed topographies where cold air tends to pool during stable, clear nights, leading to significant cooling of the road surface.

Cloud Cover and Sun Radiation

During the day, the effects of sun radiation and cloud coverage on road surface temperatures can be explained by their impact on the energy balance and the radiative fluxes received at the road surface [16]. The sun's radiation is a primary source of energy for road surfaces, directly influencing their temperature. On clear days, increased solar radiation leads to higher surface temperatures. This effect is primarily due to the direct absorption of solar energy by the road material. As the road absorbs more solar energy, it heats up, increasing the surface temperature. Meanwhile, clouds significantly modulate the amount of solar radiation that reaches the road surface. By reflecting and absorbing solar radiation, clouds can reduce the amount of energy that reaches the road, leading to cooler surface temperatures under cloudy conditions compared to clear skies. Furthermore, clouds can emit infrared radiation towards the road, which may offset some of the cooling effects, especially during heavily overcast conditions. Both relationships are linear under constant conditions, but can become non-linear when other variables such as wind speed, air temperature, and the physical properties of the road material come into play.

2.2.2 Road Surface Index (RSI)

The Road Surface Condition Index (RSI) is crucial to understanding and categorizing winter road conditions. According to the research conducted by Fu et al [17], RSI may be utilized as an alternative indicator for the friction level often seen on roadways. The index plays a crucial role in reflecting various classes of road surface condition (RSC), as outlined in the road weather information system.

RSI is especially valuable as it is derived from extensive previous field research that specifically examines the correlation between descriptive characteristics of the road surface and friction. This connection serves as the foundation for determining the threshold friction values for each type of RSC, ranging from ideal conditions (bare and dry) to highly hazardous icy conditions. Using RSI as a friction proxy is crucial to gain a more detailed understanding of road surface conditions, particularly during winter, and helps to accurately classifying and forecasting these conditions.

2.2.3 Other Influencing Factors

In addition to the above-mentioned factors, there are a few other geographical factors that may also play a significant role in influencing road surface temperatures. Two notable factors are topography and land use [18]. The elevation of a location profoundly impacts its air temperature and, consequently, the road surface temperature. Generally, as elevation increases, the temperature decreases. This is because the atmosphere is thinner at higher altitudes, which retains less heat. In mountainous regions, this can lead to significant variations in road surface temperatures, even over short distances. In addition, the type of land use, particularly the presence or absence of vegetation, impacts road conditions in theory. The Normalized Difference Vegetation Index (NDVI) has been studied for its potential effects on road surface states. However, research, such as that cited by Gu et al. (2020)[18], indicates that the impact of vegetation coverage on road surface temperatures is minimal and can often be considered negligible. This finding suggests that while vegetation can influence microclimatic conditions, its effect on road temperatures is not substantial enough to warrant major concern in road maintenance and safety strategies.

2.3 Road Condition Dynamic Segmentation

Effective road condition monitoring and maintenance require accurate segmentation of roadway sections based on varying pavement quality and safety levels. Segmentation is essential for identifying areas that require targeted interventions, optimizing resource allocation, and enhancing overall road safety. To address this need, several techniques have been developed over the years to accurately divide roadways into segments with similar characteristics.

One of the earliest and most widely adopted methods is the Cumulative Difference Approach (CDA), introduced by the American Association of State Highway and Transportation Officials (AASHTO) in 1993 [19]. CDA provided a straightforward method for segmenting pavement quality, making it a popular choice for highway and transportation authorities. However, despite its simplicity, CDA has a significant limitation: it struggles to detect boundaries between segments when the average values of both segments are lower than the overall average, leading to potential misclassification of road segments.

To overcome the shortcomings of CDA, the Wavelet Transform Approach was developed by Cuhadar et al. in 2002 [20]. This advanced technique excels in automated segmentation by identifying singularities in continuous waveforms, which are then marked as boundary points. The ability of the Wavelet Transform to detect subtle changes in road conditions has made it especially valuable in studies focused on identifying hazardous road segments. Although this approach involves complex calculations and requires careful parameter tuning for precise segmentation, it effectively addresses the limitations of CDA, offering a more robust solution for dynamic road condition segmentation.

On top of that, we also choose several widely used traditional changing point detection method, including PELT, Window Sliding, BinSeg, Bottom UP method. In addition to these approaches, there are several other clustering algorithms available. However, the methods we select have received considerable attention because of their suitability for generic data.

2.4 Gap in Research

While there has been significant research on categorizing winter road conditions using vision data, tabular data, or a combination of both, as well as on segmenting corridors to decrease road maintenance expenses and improve traffic safety, most of these studies have focused primarily on pavement conditions, specifically surface roughness, rather than on winter road surface conditions.

Researching the dynamic segmentation of winter road weather conditions is both practical and essential. First, the fluctuation in winter road conditions poses a formidable obstacle. Previous research that relies on interpolating road surface conditions between RWIS stations generally makes the erroneous assumption that human activities have no impact on road conditions. Moreover, the demarcations between various road conditions are often unclear, which requires the use of data clustering methods as a crucial component of dynamic segmentation.

Ultimately, achieving instantaneous updates on road conditions requires the incorporation of up-to-date data. Contemporary automobiles, furnished with many sensors, provide a superb reservoir of real-time data. This mitigates the constraint of stationary RWIS, which have restricted spatial coverage as a result of their fixed positions. Therefore, using data from these sophisticated vehicle sensors might greatly improve the precision and promptness of monitoring winter road conditions and implementing reaction tactics.

2.5 Summary

This chapter examines various methods for detecting and estimating road surface weather conditions, highlighting the main challenges faced by winter maintenance agencies. Research related to the detection and estimation of road surface weather conditions is broadly categorized into three primary approaches. The first involves stationary stations such as RWIS, weather base stations, mobile RWIS, and remote sensing data to infer road surface conditions. Although detailed studies and decision support systems such as Maintenance Decision Support System(MDSS) have been developed, the high costs and sparse distribution of RWIS and weather stations limit their effectiveness. The second approach uses vehicle dynamics data to measure road surface friction. This method is divided into experiment-based and model-based approaches, with vehicle dynamics-based methods providing the highest precision but requiring specialized and costly equipment. The third approach leverages machine learning and deep learning with visual data to predict road conditions. This approach has gained popularity due to the development of deep learning techniques. Research has demonstrated the feasibility of using cameras on vehicles combined with machine learning models such as SVM, random forest, and XGBoost to classify road conditions. Integrating weather data with visual data collected by dashcams has been shown to improve the accuracy and reliability of these predictions, offering a cost-effective solution to detect winter road conditions.

Additionally, the review explores factors affecting the detection of road surface weather conditions, emphasizing the role of weather conditions such as air temperature and humidity. Studies show that these factors significantly impact road surface temperatures and conditions, which are crucial for developing accurate road weather models. The RSI is identified as an important tool for categorizing road conditions, providing a proxy for friction levels based on extensive field research.

The dynamic segmentation of road conditions is also discussed, tracing the evolution from the CDA to more advanced methods like the Wavelet Transform Approach and machine learning techniques such as Fuzzy C-Mean Clustering. These methods improve the precision of road segmentation, particularly for identifying hazardous road segments.

Finally, the review identifies gaps in current research, noting that while significant work has been done on pavement conditions and segmentation, there is a lack of focus on winter road weather conditions. The need for real-time data from modern vehicles equipped with sensors is emphasized to improve the accuracy and timeliness of winter road condition monitoring and response strategies.

Chapter 3

Methodology

3.1 Proposed Method

The technique of this research is divided into two independent portions in order to meet the criteria for a real-time road status map (as shown in Figure (3.1)). The first phase is to create a vehicle system with the ability to instantly gather and estimate current road conditions. The second part consists of determining a suitable approach to data aggregation to enable complete automation and dynamic segmentation in real time. This research uses many data sources, such as dashcam video footage from automobiles, vehicle sensor information acquired using OBD interfaces, and synchronized collection of RWIS (Road Weather Information Systems) data from the study region.

3.2 Identification of Road Conditions

This work utilizes deep learning to extract features for the efficient real-time categorization of road surface information obtained from dashcams. Consequently, to improve the precision of our model, we have chosen to use a fusion strategy. This involves the integration of vehicle-measured tabular data and RWIS data with the collected photos. Subsequently, machine learning approaches are used for the final classification procedure.

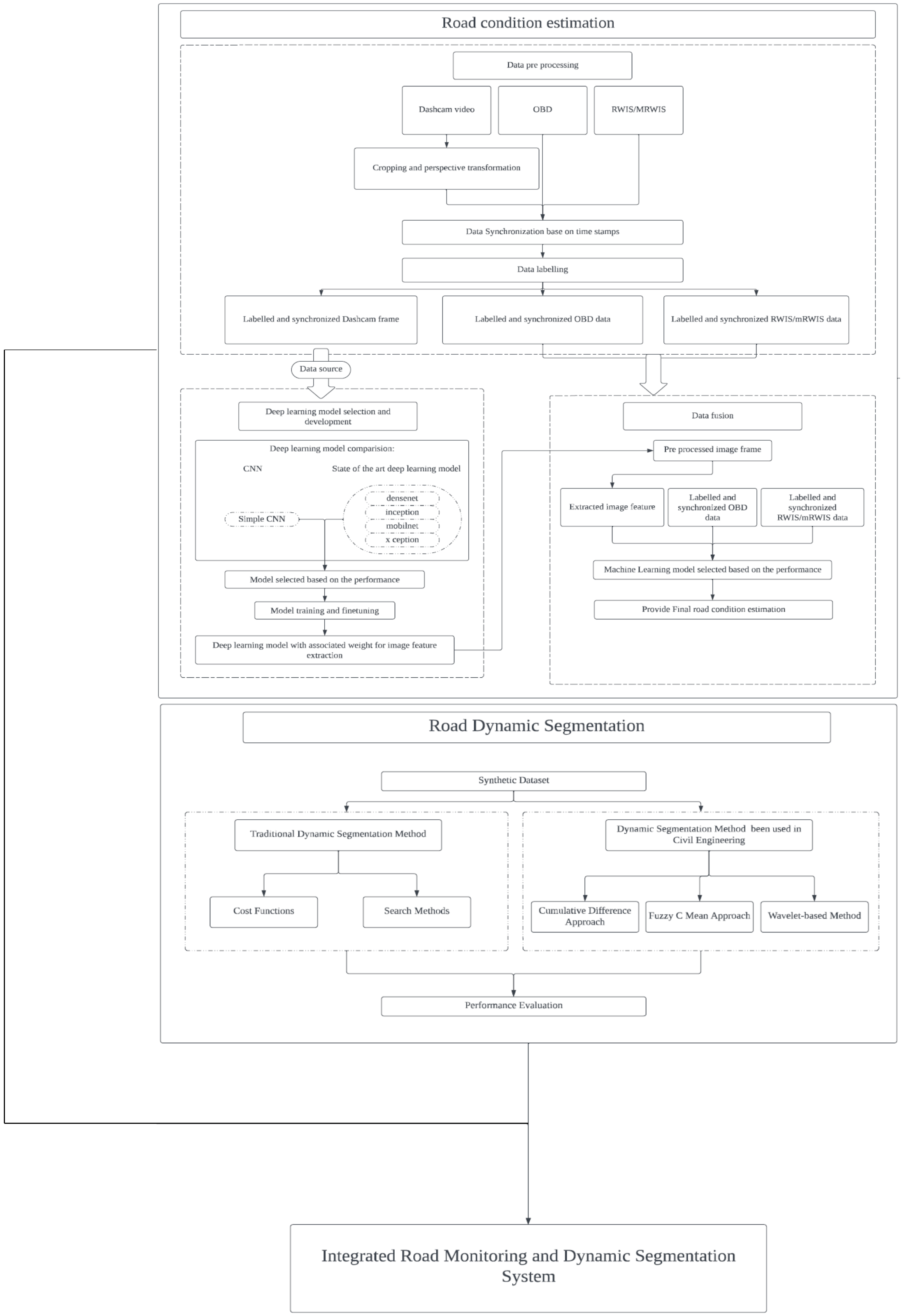


Figure 3.1. Methodological Framework: Research Process Flowchart

3.2.1 Deep Learning Method

Deep learning has revolutionized the field of image classification, resulting in significant improvements in both accuracy and efficiency. As a branch of machine learning, neural networks with numerous layers are utilized to analyze and comprehend large amounts of intricate data. These complex neural networks are very good at recognizing patterns and characteristics in images, which makes them very suitable for image categorization [21]. The primary benefit of deep learning is its capacity to acquire hierarchical feature representations directly from the data, eliminating the need for human feature extraction. This sets it apart from conventional machine learning methods. The model's capacity to train autonomously allows it to adjust and enhance its precision as it analyzes more data, which is particularly advantageous in the constantly changing field of picture data. Deep learning has emerged as a fundamental approach in several modern image classification applications, including face recognition systems and medical image diagnostics. Its exceptional ability to effectively process the complex details of visual input is the reason for its widespread use.

The method of categorization in deep learning often involves the use of complex artificial neural networks, which consist of layered structures and play a crucial role in their functioning. The network consists of an input layer that accepts raw data, such as pixel values in image classification, numerous hidden layers, and an output layer. The hidden layers, consisting of several neurons, gradually extract and enhance characteristics from the input data. The first layers may detect fundamental components like edges or colors, while the deeper layers understand intricate aspects such as forms or unique objects. The output layer commonly employs an activation function to build a probability distribution over the specified classes. The model's classification is then chosen by the class with the greatest probability. The training process of these models entails the execution of forward propagation, where data is sent through the network and modified at each step, subsequently followed by back propagation, where the model adapts its weights according to the error computed by a loss function at the output.[22] The model may enhance its predictions via an iterative process, often guided by optimization methods such as stochastic gradient descent. Convolutional Neural Networks (CNNs) are often used in image classification tasks because of their specialized topologies. CNNs efficiently process spatial data using convolutional and pooling layers, allowing them to effectively capture spatial hierarchy in pictures. Deep learning offers a sophisticated and potent method for classification tasks, particularly in the analysis and categorization of complicated picture data, due to its intricate architecture and learning processes.

Convolutional Neural Network

Our research utilizes the finely calibrated basic CNN model that was successfully used in feature extraction from roadside cameras, as evidenced in the earlier work by Juan. (2019) [23]. This model is particularly designed to proficiently tackle intricate picture categorization jobs. The procedure begins with an initial 2D convolutional layer that has 16 filters of 3x3 size. It uses the ReLu activation function, which is ideal for handling input pictures of resolution 224x224 with 3 channels (RGB). The design thereafter advances via a succession of convolutional and max pooling layers, with the number of filters in these convolutional layers progressively increasing in the order of 27, 46, 79, and 134. This configuration efficiently captures the characteristics of the picture while also decreasing the spatial dimensions, hence improving computing efficiency.

The model also includes a dropout layer with a 50% rate after the convolutional and pooling layers to reduce overfitting. Following this, there is a flattening layer that transforms 2D matrices into vectors. The input is then sent through a sequence of dense layers with 24 and 12 neurons, respectively. Both of these layers use the "relu" activation function. The design is completed by the output layer, which consists of a dense layer with 3 neurons. These neurons represent the classification categories and use a 'softmax' activation function to generate a probability distribution across these classes. The CNN framework is designed with multiple layers of convolution and pooling to extract features from images. It also includes dense layers for classification and strategically incorporates dropout layers to improve computational efficiency and prevent overfitting.

On top of Juan's method, our study also explores the integration of methodologies from Gessert et al., who employed a purely deep learning-based approach for classifying skin lesions using CNNs to process both visual and tabular data. Their method, which successfully handled various challenges such as class imbalances and integration of multimodal data, inspired us to adapt our model to combine these advanced techniques with the existing CNN framework. By incorporating elements from both Juan and Gessert et al., we aim to create a more versatile and robust system capable of tackling complex image classification tasks with enhanced precision.

Transfer Learning

Transfer learning has become a powerful method in the changing field of image categorization, often outperforming traditional convolutional neural networks (CNNs) in terms of potential. The primary advantage of transfer learning resides in its capacity to use pre-trained models on extensive and varied datasets, such as ImageNet. Pre-training provides the models with strong fundamental knowledge, allowing them to quickly adapt to particular tasks even with little data. This is especially beneficial in situations where obtaining substantial amounts of training data that are unique to the job is difficult. Moreover, transfer learning effectively tackles a significant issue in picture classification: the potential for overfitting, particularly when dealing with less complex datasets. By using pre-trained models, the need for rigorous training on a short dataset is significantly decreased, therefore reducing the chances of the model acquiring irrelevant information and abnormalities that are unique to the smaller dataset. We conducted an experimental study using well-known transfer learning architectures, including ResNet50, VGG16, Inception, and MobileNet. Each model has distinct architectural advantages, making them appropriate for a range of picture categorization applications. In accordance with the suggestion made by Juan (2019) [23], we used a strategic methodology for implementing transfer learning by adjusting the percentage of layers that were kept fixed in these models. This approach entails the targeted freezing of a certain proportion of the layers, particularly those located at the beginning of the network, which often play a crucial role in collecting fundamental and widely applicable characteristics of pictures. The subsequent layers, which are more suitable for classification tasks, are kept trainable. The objective of this strategy is to achieve an ideal equilibrium by using the pre-existing information of the models and refining them to suit our particular dataset. Through this approach, we want to optimize the possibility of discovering the best appropriate model setup for our objective.

3.2.2 Machine Learning

Part of this research also utilizes machine learning approaches to fuse image features and tabular data more effectively, thus improving the accuracy of the final prediction. Therefore, we chose three of the most frequently used machine learning approaches for application and analysis. The approaches mentioned include SVM, regression trees, and random forests. Each of these methods has unique benefits and operating mechanisms, making them especially appropriate for the intricate tasks of categorizing features and optimizing prediction accuracy in various data settings.

Regression Tree

Regression trees [24] are decision trees that are especially tailored for predictive modeling in the fields of data mining, machine learning, and statistics. Their functioning involves partitioning a dataset into smaller subsets, which are easier to handle, using decision rules generated from the attributes of the dataset. The rules constitute the nodes of the tree, where each leaf node represents a numerical value, usually the average of the target variable for that particular segment. The procedure begins at the foundation, dividing the data set into binary subsets according to unique properties. The main objective of each split is to decrease the variability within each resulting subgroup. The process usually involves choosing the feature and a threshold that effectively distinguishes the data; however, other criteria such as mean squared error may also be used.

Data splitting and tree construction techniques and criteria are essential in the theory of regression trees. The fundamental principle is variance reduction, wherein the algorithm assesses each prospective split by quantifying the extent to which it would decrease the total variance, with the objective of maximizing this reduction. This entails evaluating the difference in variability of the desired outcome variable throughout the full dataset in comparison to the combined variability of the two subgroups formed after the split, taking into account their respective sizes. The split that yields the greatest reduction in overall variance is selected, guaranteeing that the resulting subsets are as similar as feasible. To minimize overfitting and the creation of too deep and complex trees, it is crucial to include stopping criteria, such as a maximum tree depth or a minimum amount of samples in a leaf. These criteria are crucial for preserving an equilibrium between the tree's depth and its capacity to apply to various datasets.

Although regression trees have benefits and are valuable, they also have limitations. An important obstacle in their implementation is the inclination to excessively match the training data, especially if the tree is allowed to expand without limitations. Methods like pruning and imposing restrictions on tree depth or minimum sample splits are often used to address this problem. Another issue is their susceptibility to variations in the training dataset. As a consequence of their hierarchical nature, even slight changes in the data might cause variations in the divisions, which may ultimately lead to a substantially different tree configuration. The sensitivity of the model prompts inquiries about its coherence and robustness across various datasets. Furthermore, while regression trees are easily understandable, they may exhibit reduced predictive capability in some situations when compared to more intricate models such as random forests or gradient-boosting machines. Nevertheless, the efficacy of a regression tree may differ significantly depending on the dataset. In some instances, a finely tuned regression tree might exhibit comparable performance to these more advanced models.

Random Forest

Random forests [25] are a more advanced kind of ensemble learning method that rely upon the principles of regression trees. A Random Forest is a compilation of Decision Trees, usually Regression or Classification Trees, that functions based on the concept of 'collective intelligence.' This approach involves cultivating several trees and consolidating their forecasts to get a conclusive determination. The primary advantage of a Random Forest is its capacity to mitigate the problem of overfitting, which is often seen in individual Regression Trees, by averaging the outcomes of several trees. The use of an ensemble strategy significantly improves the overall forecast accuracy and resilience of the model. Similar to Regression Trees, Random Forests provide the ability to capture intricate, nonlinear connections and are highly interpretative, since each unique tree provides valuable understanding of the data. Nevertheless, via the amalgamation of predictions from several trees, Random Forests often attain superior accuracy and stability compared to a solitary Regression Tree, particularly in situations involving a significant volume of data and characteristics. Random forests function by creating several decision trees throughout the training process and producing the class that represents the most often occurring class (in classification) or the average prediction (in regression) of the individual trees. The algorithm begins by using bootstrapping, a technique that randomly selects sections of the training data and attributes to construct several trees. The inclusion of randomization not only guarantees a wide range of variation among the trees but also enhances the resilience of the whole model. The mathematical representation of Random Forests may be seen as an expansion of the ideas used in Regression Trees. Every tree in the forest generates a prediction by considering the features, and the final output is obtained by combining these predictions. The principle of reducing variance, as applied in Regression Trees, is employed in each tree of the forest. However, the aggregation process further decreases the variance, resulting in a model that is more precise and reliable. Feature bagging, which involves randomly selecting features at each split point, introduces an additional level of variance reduction. This makes the model less sensitive to individual characteristics and more generic in its predictions. Although Random Forests effectively overcome certain constraints of Regression Trees, they also present their own distinct issues. Random Forests have a significant benefit over single Regression Trees in that they are less prone to overfitting. Random Forests improve their ability to generalize to unknown data by aggregating the outputs of numerous trees. Nevertheless, this benefit is accompanied by a rise in computational complexity and resource demands, particularly as the number of trees in the forest expands. An additional benefit is their capacity to efficiently manage extensive datasets with several characteristics; however, this also results in a more intricate and less comprehensible model compared to a single Regression Tree. While the decision-making process in Regression Trees is readily viewed and comprehended, the decision process in a Random Forest may be opaque, rendering it a "black box" in certain applications. Furthermore, the process of selecting hyperparameters, such as the quantity of trees and the depth of each tree, needs meticulous adjustment in order to get the best possible performance, which may be a laborious task.

Support Vector Machine

Support Vector Machines (SVMs) [26] are a resilient and adaptable category of supervised learning algorithms, primarily used for classification jobs, but also suitable for regression difficulties. SVMs operate on the core premise of identifying a hyperplane inside a multidimensional space that effectively separates the data points into discrete categories. The hyperplane is chosen to optimize the separation between data points belonging to various classes, which is crucial for the efficacy of SVM. Data points that have the shortest distance to the hyperplane and significant impact on its location and orientation are referred to as support vectors, thus giving the procedure its name. SVMs are highly regarded for their capacity to handle high-dimensional data and their effectiveness in scenarios where the number of dimensions exceeds the number of samples. As a result, they are particularly well-suited for intricate categorization tasks, such as identifying and categorizing text and images. Moreover, SVMs are less susceptible to overfitting, particularly in scenarios with a large number of dimensions, since they rely heavily on support vectors and prioritize maximizing the margin. SVMs provide a notable benefit in their ability to choose the kernel function, allowing them to adjust to various data distributions and connections by transforming input data into feature spaces of high dimensions. SVMs use a unique approach to categorize data points by using hyperplanes. The ideal hyperplane is characterized as the hyperplane with the largest margin, which represents the maximum distance between the hyperplane and the nearest data point of any class. In mathematical terms, this involves solving a quadratic optimization problem to maximize the margin while still guaranteeing an accurate classification of the data points. The given optimization issue may be formulated as the task of minimizing.

$$\frac{1}{2}\|w\|^2$$

$$\text{subject to} \quad y_i(w \cdot x_i + b) \geq 1 \quad \text{for all } i$$

The given inequality constraint states that the product of the weight vector and the training samples, plus the bias, must be greater than or equal to 1 for all training samples, where the class labels are denoted as y_i. The kernel technique, a fundamental feature of SVM, enables the method to function in a high-dimensional environment without needing to explicitly calculate the coordinates of the data points in that space. In contrast, the kernel function calculates the dot products of the data points in the feature space, allowing SVMs to effectively manage intricate nonlinear connections by selecting suitable kernels such as polynomial, radial basis functions (Rbf), or sigmoids. Although SVMs provide notable advantages, they also exhibit certain constraints. A major obstacle in using SVMs is the choice of a suitable kernel and its associated parameters, since these factors may greatly impact the algorithm's performance. The process of selecting typically requires expertise in a certain field and the use of trial and error, since there is no universally applicable answer. A further constraint is the computational efficacy, particularly when dealing with extensive datasets. SVMs may be computationally demanding, which limits their practicality in situations involving large datasets. Furthermore, SVMs lack intrinsic probabilistic capabilities and therefore cannot provide probability estimates for classifications. This limitation may be problematic in situations where the ability to assess the confidence of predictions is vital. Finally, while SVMs effectively handle high-dimensional data, they may encounter difficulties when dealing with very vast feature spaces or datasets containing substantial noise. This is because the distinct separation margin may not be there or may result in overfitting when noisy data are included.

3.3 Dynamic segmentation

The intrinsic fluctuation of road weather conditions has been a consistent problem in the industry, namely in updating road conditions in real-time and accurately determining their limits. The various weather conditions on the road, including dry, rainy, and snowy conditions, have a considerable influence on both road safety and traffic efficiency. Therefore, it is crucial to create accurate and rapid techniques for assessing road conditions. A substantial body of literature has been produced on this topic, presenting several answers to this intricate problem.

Considering the varied characteristics of these techniques and the special demands of our project, which aims to integrate real-time data processing with the highest level of accuracy and dependability, we have chosen to concentrate on three widely used methods of dynamic segmentation. The selection of these strategies was based on their relevance to the data formats we are dealing with and their demonstrated efficacy under comparable circumstances. Dynamic segmentation refers to the act of dividing road networks into parts depending on changing circumstances, enabling a more detailed and accurate portrayal of road weather conditions. Adopting this method is essential for creating models that can adjust and react to the changing conditions of road settings. This will improve the accuracy of the predictions and the effectiveness of weather-sensitive road monitoring systems.

3.3.1 Traditional Changing point detection

Traditional change point detection has been extensively studied, focusing on three key elements: the cost function, the search method, and constraints. These components play a crucial role in recognizing changes in the statistical features of time series or data sequences, offering a systematic method to detect and pinpoint these changes.

Cost Function

Cost functions play a vital role in Change Point Detection tasks, as they quantify the level of agreement between a segmented signal or data points and a model. They effectively assess how well the model explains the data.[27], The fundamental cost function is expressed by equation (3.1),

$$minJ(\mathcal{T}, y) := \sum_{k=0}^{K} c\left(y_{t_k..t_{k+1}}\right) \tag{3.1}$$

where the criterion function $J(\mathcal{T}, y)$ is designed to achieve optimal segmentation by minimizing over segments, with K denoting the number of segments.This situation can be divided into two cases: one where the segment numbers are known but their positions are unknown, and another where both the numbers and locations of the segments are unknown. In the second case, a punishment function, denoted $pen(\mathcal{T})$, is required and will be addressed in later sections.

Cost functions vary widely and are categorized based on the structure and characteristics of the data, serving either parametric models, which define variable relationships through a fixed number of parameters, or non-parametric models, which do not assume a predefined form and adapt to data characteristics. Given the randomness in winter road conditions due to factors like weather and maintenance, this study opts for cost functions associated with non-parametric models, specifically Kernel-based, Mahalanobis distance-based, and Rank-based cost functions.

When dealing with numerical data, it is typical to use linear kernels for parametric data and Gaussian kernels for complicated nonparametric data[27]. This study employs a cost function based on a Gaussian kernel (radial basis function), which is well-suited for nonparametric data characteristics. The function is written as follows:

$$c_{rbf}\left(y_{a..b}\right) := (b-a) - \frac{1}{b-a} \sum_{s,t=a+1}^{b} \exp\left(-\gamma \left\|y_s - y_t\right\|^2\right) \tag{3.2}$$

In equation (3.2), the variable $y_{a..b}$ denotes a contiguous subset of observations ranging from position a to position b in the series. The parameter γ is a positive scaling factor that determines the width or sensitivity of the Rbf kernel to the similarity between data points. It is sometimes referred to as the bandwidth parameter. The expression $\left\|y_s - y_t\right\|^2$ denotes the squared distance between two data points.

Mahalanobis distance-based cost functions, derived from parameterized versions, integrate the ideas of Reproducing Kernel Hilbert Space (RKHS) denoted as H, and a symmetric positive semi-definite matrix denoted as M. This adaption improves the capacity to analyze non-parametric data without depending on specific assumptions about the distribution of the data. As a result, it accurately measures and identifies points of change within the dataset. The function of this method is defined as

$$c_{\mathcal{H},M}\left(y_{a..b}\right) := \sum_{t=a+1}^{b} \left\|\phi\left(y_t\right) - \bar{\mu}_{a..b}\right\|_{\mathcal{H},M}^2 \tag{3.3}$$

where

$$\left\|\phi\left(y_s\right) - \phi\left(y_t\right)\right\|_{\mathcal{H},M}^2 = \left(\phi\left(y_s\right) - \phi\left(y_t\right)\right)' M \left(\phi\left(y_s\right) - \phi\left(y_t\right)\right) \tag{3.4}$$

In equation (3.3), $\mu_{a..b}$ represents the mean embedding in the Reproducing Kernel Hilbert Space (RKHS) of all transformed data points $\phi(y_t)$ from time point a to time point b.

Last but not least, Rank based cost functions can be expressed by equation (3.5),

$$c_{rank}\left(y_{a..b}\right) := -(b-a)\bar{r}'_{a..b}\widehat{\Sigma}_r^{-1}\bar{r}_{a..b} \tag{3.5}$$

where r can be defined as,

$$r_{t,j} := \sum_{s=1}^{T} \not\Vdash\left(y_{s,j} \leq y_{t,j}\right) - \frac{T+1}{2}, \quad \forall 1 \leq t \leq T, \forall 1 \leq j \leq d \tag{3.6}$$

and $\widehat{\Sigma}_r$ is defined as,

$$\widehat{\Sigma}_r = \frac{1}{T}\sum_{t=1}^{T}\left(r_t + 1/2\right)'\left(r_t + 1/2\right) \tag{3.7}$$

Searching Method

The search methods in change point detection can be classified into two categories: optimum and approximate detection approaches. Optimal techniques, such as PELT, produce accurate segmentation results, whereas approximate techniques such as window sliding, binary segmentation, and bottom-up segmentation provide feasible alternatives when the computational complexity of optimum techniques is too high, but there may be a potential decrease in accuracy.

PELT The PELT method is designed to address the challenge of changepoint detection. Specifically, it is capable of autonomously identifying changepoints within a time series without a predetermined number of changepoints [28]. Initially, a penalty function is determined, and for a new time point to be classified as a changepoint, the reduction in segmentation cost attributed to this point must exceed the penalty value. If the reduction in segmentation cost is less than the penalty, the overall cost will increase, thereby disqualifying the new time point from being considered a changepoint. The logic of the pruning rule can be formulated as follows.

if $[\min_{\mathcal{T}} V(\mathcal{T}, y_{0..t}) + \beta|\mathcal{T}|] + c(y_{t..s}) \geq [\min_{\mathcal{T}} V(\mathcal{T}, y_{0..s}) + \beta|\mathcal{T}|]$ then t is not the last change point

Approximate Techniques All approximate techniques share the same fundamental: based on their sequential and iterative character, enabling a gradual estimation of change points in a data set. Contrary to optimal techniques that handle the complete dataset at once, these methods produce a solitary estimation of a changepoint throughout each iteration, progressively improving the accuracy of the changepoint's position with each succeeding iteration. This procedure entails either introducing novel estimations or modifying current ones. The versatility of these approaches becomes apparent when the value of the number of changepoints, denoted as K^*, is known. This allows the algorithm to iterate a specific number of times to determine the exact number of change points. On the other hand, if the value of K^* is not known, the iterations will keep going until a suitable stopping condition is met. In practical terms, this implies that although approximate approaches may not detect all changepoints or reach the same level of accuracy as optimal methods, their computational efficiency makes them well-suited for analyzing big datasets or for when there are limitations on processing resources.

Constrain

To avoid increasing complexity and considering that linear penalty functions are the most commonly used in other studies [28], this research focuses solely on linear penalties, which expressed as (3.8)

$$\mathrm{pen}_{l_0}(\mathcal{T}) := \beta|\mathcal{T}| \tag{3.8}$$

where $\beta > 0$, A higher β value results in fewer segments, while a lower β increases the number of segments, potentially making them more susceptible to noise influence.

3.3.2 Changing Point Detection in Civil Engineering Field

In the field of civil engineering, research since the 1990s has been dedicated to developing improved change point detection methods to segment road conditions. The earliest method, the Cumulative Difference Approach (CDA), was introduced by the American Association of State Highway and Transportation Officials (AASHTO) in 1993 [19] and quickly gained popularity for its simplicity and effectiveness. However, after 2000, many researchers recognized that CDA has many limitations [29][30][31], such as its inability to detect multiple segments with different average response levels and its sensitivity to changes in the parameters of road conditions, leading to the proposal of new methods. Table (3.1) shows the methods that have been developed over years.

Three approaches stand out from the rest in terms of data types that are relevant to our research: the cumulative difference technique, the wavelet-based method, and Fuzzy c-mean clustering. Among these, Fuzzy c-mean clustering requires prior knowledge of the number of segments, rendering it unsuitable for our context. Consequently, we focus solely on the CDA and wavelet-based methods.

Cumulative Difference Approach

CDA is a very straightforward method among all change-point detection methods. Figure (3.2) illustrates the process of using CDA to determine the change point of

Table 3.1: Changing point detection method in Civil Engineering field

Study	**Methods**	**Response Variable**
Divinsky et al. (1997)	CDA	Roughness, Generic
Ping et al. (1999)	CDA and significance testing	Rut
Cuhadar et al. (2002)	Wavelet based method	Generic
Misra and Das (2004)	CART	Roughness
Tejeda et al. (2008)	Accumulated sum (CUSUM)	Skid Resistance
Yang et al. (2009)	Fuzzy c-mean clustering	Pavement Condition Rating
D'Apuzzo and Nicolosi (2012)	Various Methods	Skid Resistance
Abdelaty and Jeong (2018)	affinity propagation clustering method	IRI and rutting

the pavement distress value, where (a) represents the actual pavement distress value, (b) shows the cumulative area, and (c) shows the comparison between the cumulative area and the average value.

In general, it contains three parts: calculating the cumulative area at any point within the profile and determining the cumulative difference by comparing the actual cumulative area to the average, identifying unit boundaries where the slope of this difference changes sign, and highlighting transitions between homogeneous units. The cumulative difference can be shown as follows:

$$Z_x = \sum_{(i=1)}^{n} a_i - \frac{\sum_{i=1}^{n} a_i}{L} \sum_{i=1}^{n} x_i \tag{3.9}$$

Where a_i is the interval area,

$$a_i = \frac{(r_{i-1} + r_i) \times x_i}{2} \tag{3.10}$$

In equation (3.9) and (3.10), n is the n^{th} pavement response measurement, r is the value of the pavement response and L is the total length of the corridor.

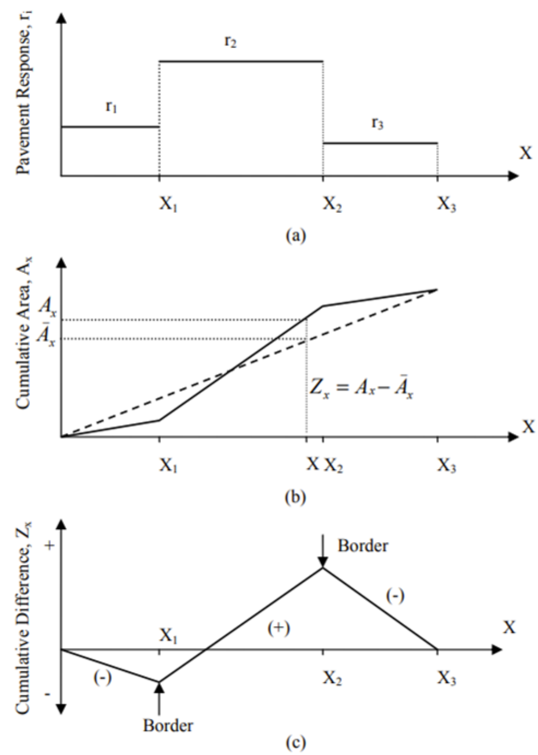


Figure 3.2. CDA approach illustration [19]

Wavelet-theory-based Approach

Introduced by Cuhadar [20] and further validated by Boroujerdian [32], the wavelet-theory-based approach to the detection of change points is highly effective for autonomously identifying boundaries within road condition datasets. In general, the method can be described in the following steps: 1. This method begins by transforming data that is not evenly distributed in space into a spatial framework that is evenly distributed using equation (3.11), establishing a consistent foundation for further research.

$$FL = \left(1 - \frac{x}{\Delta}\right) F \text{ and } FR = \left(\frac{X}{\Delta}\right) F \tag{3.11}$$

where we assume Δ is the distance of the uniform point on the grid (minimum segment), x is the distance between the measurement and the point on the left grid and $\Delta - x$ is the distance between the measurement and the point on the right grid.

2. The approach then detects major changes at different scales using the continuous wavelet transform. This is critical for accurately recognizing subtle transitions within the data. This capacity is improved by using high-frequency filters to remove noise, hence enhancing the emphasis on significant signal modifications.

The continuous wavelet transform can be defined as (3.12)

$$W_\psi f(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} f(x)\psi^* \left(\frac{x-b}{a}\right) dx \tag{3.12}$$

where a controls the window width, b is the position of the wavelet, and $f(x)$ is the road surface condition data.

In our research, ψ^* represents the chosen wavelet. We opt for the Mexican hat wavelet due to its high variance, making it suitable for edge detection purposes. Furthermore, its spatial localization properties enable the analysis of signals at various scales, facilitating the detection of multiscale features. The ψ^* is then defined as[33] (3.13)

$$\psi(x)=\frac{2}{\sqrt{3}\sqrt[4]{\pi}}\left(1-x^2\right)e^{-\frac{x^2}{2}} \tag{3.13}$$

3. Ultimately, by identifying the central point and boundaries of various road conditions, we can determine the position and boundaries of each segment, thereby achieving segmentation of the road condition.

3.4 Ordinary Kriging

Kriging, initially applied in estimating mineral content, has gained widespread use in various fields such as geology, hydrology, and environmental science due to its high accuracy and relative simplicity.[34][35]It is particularly valuable for estimating values at unmeasured locations. Among its types, ordinary kriging (OK) is favored for its simplicity compared to universal kriging and regression kriging, and for its increased effectiveness compared to simple kriging, making it our choice for interpolating RWIS data. This approach serves two main purposes: comparing with vehicle sensor data and supplementing critical data for road condition forecasts not available from vehicles.

According to a previous study [36], the OK estimator can be written as:

$$\hat{Z}(x)=\sum_{k=1}^{m}\lambda_k(x)Z\left(x_k\right)+\left[1-\sum_{k=1}^{m}\lambda_k(x)\right]m(x) \tag{3.14}$$

Here, $\hat{Z}(x)$ represents the estimated value at an unmeasured site, $m(x)$ is the mean of the random variable $Z(X)$, and λ_K is the weight applied to $Z(X_k)$ for the estimation location x.

For Ordinary Kriging, the covariance model is pivotal, encapsulated by the semi-variogram equation (3.15)

$$\hat{\gamma}(p)=\frac{1}{2n(p)}\sum_{k=1}^{n(p)}\left[z\left(x_k+p\right)-z\left(x_k\right)\right]^2 \tag{3.15}$$

where $\hat{\gamma}(p)$ denotes the estimated semivariogram for a lag distance p, with $n(p)$ representing the count of observation pairs separated by this distance. This model quantifies the spatial dependency, which is crucial for the interpolation's precision.

3.5 Summary

This chapter provides an overview of the methods and algorithms used in this thesis. We explored the use of basic Convolutional Neural Networks and pre-trained models using transfer learning to augment accuracy in the process of extracting picture data. To improve accuracy, our strategy involves merging these characteristics with meteorological data and using machine learning classification methods. We have selected regression trees, random forests, and support vector machines, all of which have been previously studied in terms of their advantages, disadvantages, and underlying concepts. In order to monitor winter road surface conditions in real-time, we are using a technique called dynamic segmentation. This method involves dividing the roads into segments depending on their conditions, with the goal of grouping together areas with similar surface characteristics and identifying any changes that occur. Finally, as a result of insufficient vehicle sensor data, we are contemplating the use of the kriging technique, which involves employing RWIS data to deduce the absent information.

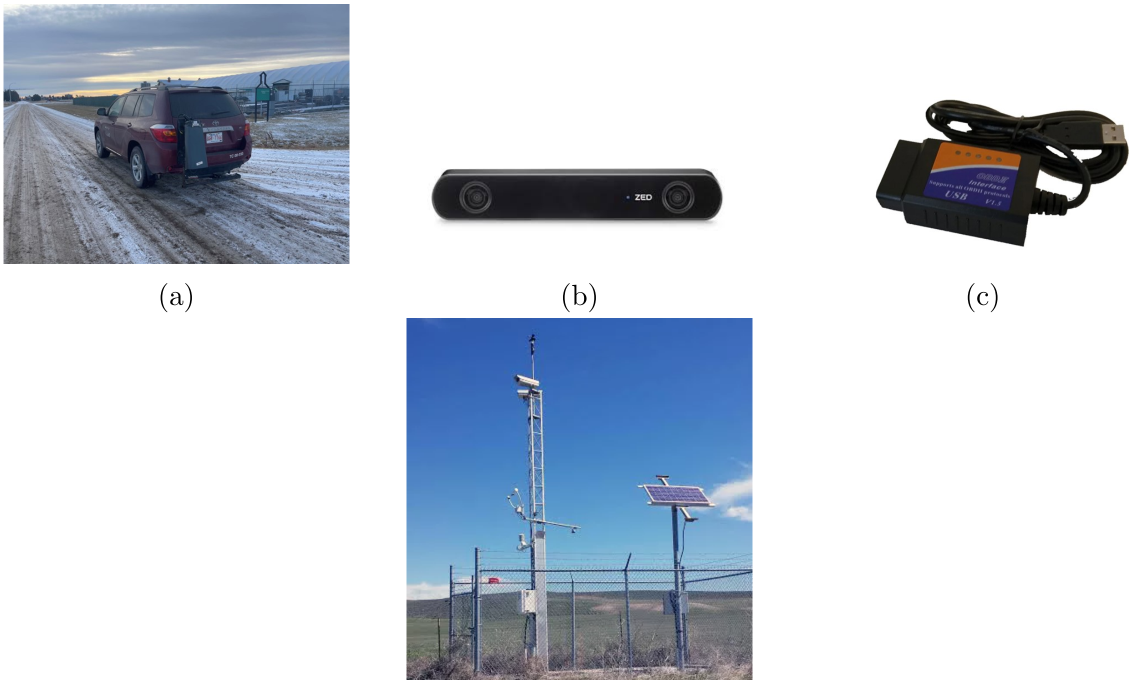
Chapter 4

Case Study

4.1 Data Description and Pre-Processing

This study was conducted on Highway 2, south of Edmonton, Alberta, which was selected due to its high latitude (53.5461° N) and significant snowfall during winter. These conditions are typical of northern climates, making them an ideal proxy for assessing winter road safety technologies. The data collection system consisted of a test vehicle equipped with a MRWIS, a Zed2 dashcam to capture front vehicle images, and an OBDII USB adapter for real-time vehicle data collection. RWIS data, crucial for obtaining accurate meteorological conditions on the road, was collected simultaneously with vehicle data and front imagery to ensure temporal consistency through the 511alberta API.

Our data collection efforts in the winter of 2022-2023 encountered several challenges, primarily unpredictable weather and technical limitations of our equipment, which led to only four successful data collection sessions. Each session followed a predetermined route starting from Southgate mall, moving south along Gateway Blvd, onto Highway 2, and then returning from Red Deer. The sessions were carefully planned to capture a range of conditions: from the dry road conditions on the morning of March 4 to the snow-covered roads in the subsequent sessions on March 11 and 18. This variability in road conditions was essential for testing the responsiveness of our data collection setup under different environmental stresses.



(a) (b) (c)

(d)

Figure 4.1: (a) mobile RWIS unit. (b) ZED II camera. (c) ELM327 OBD-USB adapter. (d) RWIS station

4.1.1 Vision Data

Initially, video frames were directly extracted from dashcam footage and classified into three classes: bare / dry, partially covered snow, and fully covered snow to construct a dataset using image-level labeling. Despite the high training and validation with deep learning, the precision of real-world applications dropped to around 70% (depicted in Figure (4.3a)), indicating severe overfitting. Further analysis of the model's penultimate layer revealed a focus on cloud-like features rather than the road (4.3b), underscoring the importance of cropping images to direct the model's attention to road conditions. Based on this, we decided to crop the frames captured by the dashcam to focus solely on the road surface. To standardize the data and ensure accurate cropping of the road surface, we initially used cones to determine the cropping coordinates, as illustrated in Figure (4.4).

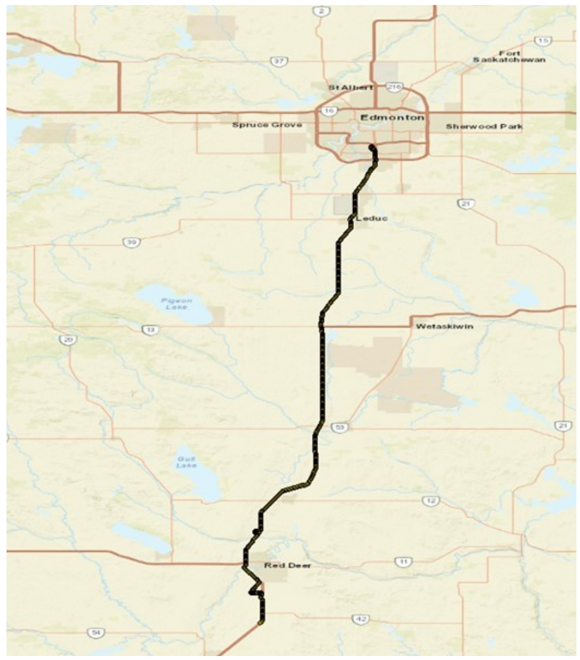
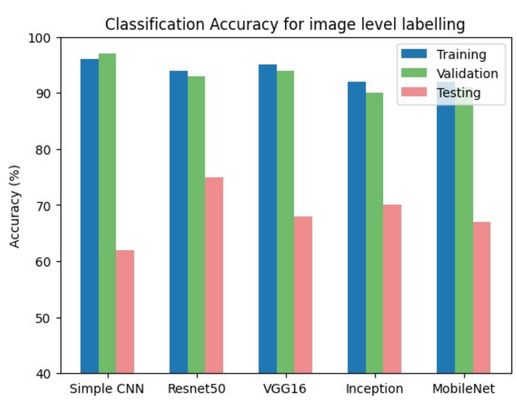
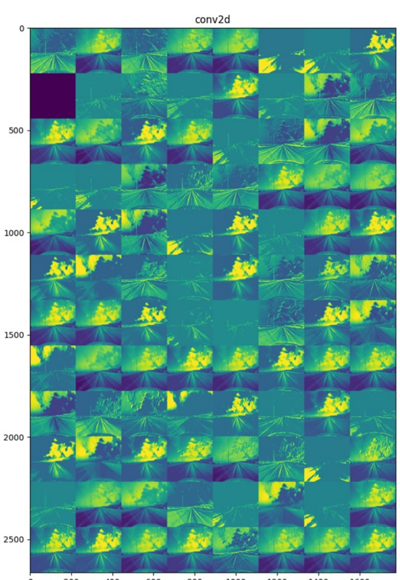


Figure 4.2: Data collection route



(a) Image-level labeled dataset show very low accuracy on test dataset



(b) CNN focus on the sky instead of the road

Figure 4.3: Analysis of model performance and focus areas

Figure 4.4: cones are arranged in a 7.5 meter by 7.5 meter square, located 15 meters ahead of the vehicle.

Subsequently, to facilitate the integration of these images into deep learning models, we performed a perspective transformation on the cropped images and resized them to 224x224 pixels for efficient processing.

(a) Dry (b) Partially covered (c) Fully covered

Figure 4.5: Analysis of model performance and focus areas

4.1.2 Tabular Data

The tabular data encompasses dozens of vehicle sensor data collected via OBD and 12 MRWIS parameters. Drawing on previous research[23], we selected potential pre-

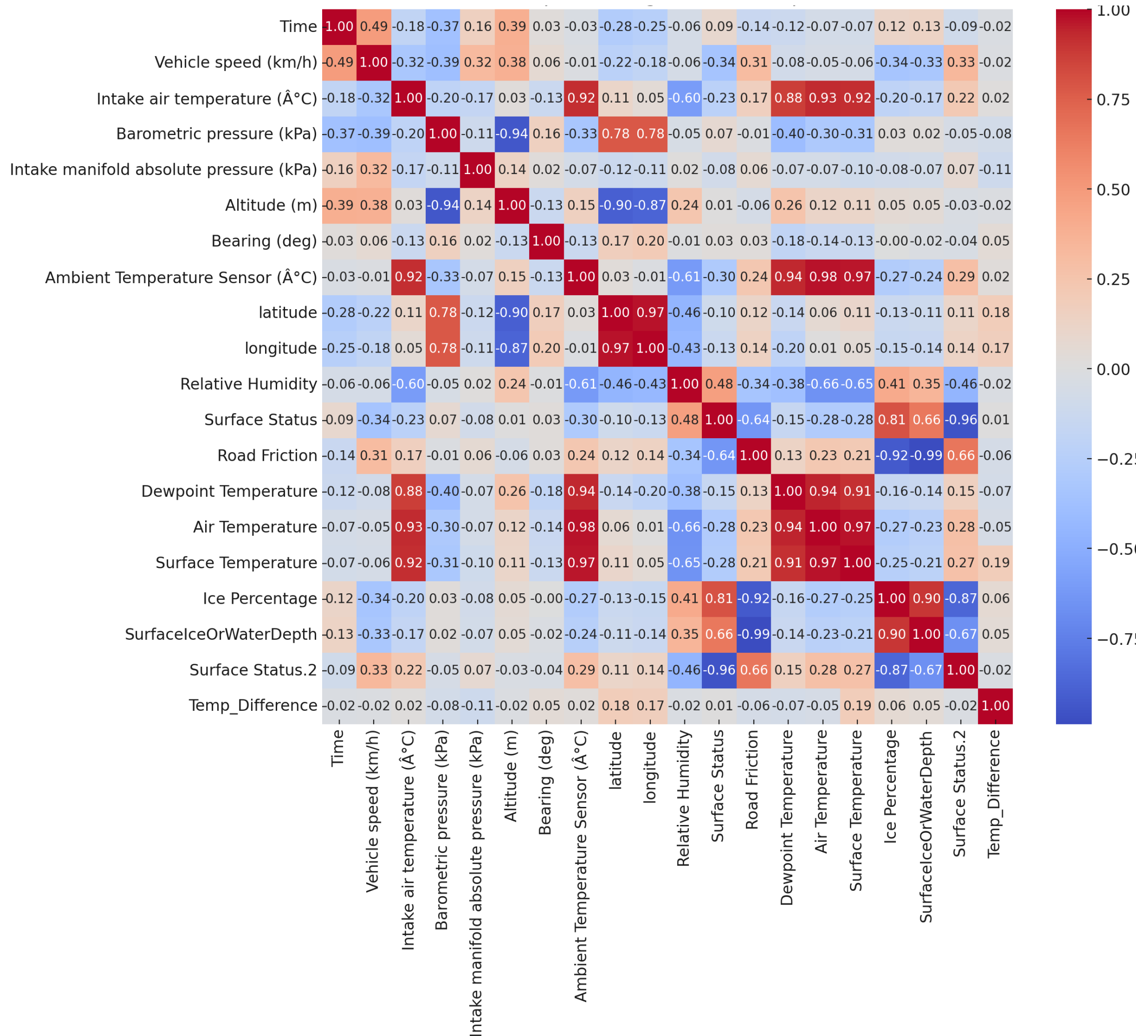


Figure 4.6: correlation heatmap of the potential predictors

dictors of road surface conditions and performed correlation tests to evaluate their predictive utility. (4.6)

We collected a grand total of 10,728 completely synced data items. During the first processing phase, we transformed each category into numbers ranging from 0 to 6 to enable the inclusion of descriptive factors such as surface state in the correlation analysis. A value of 0 was assigned to indicate bare conditions, while a value of 6 was assigned to reflect ice circumstances.

The correlation heatmap indicated a strong positive association (coefficient of 0.805) between the percentage of ice and the surface state. This aligns with the intuitive hypothesis that higher percentages of ice correlate with icier road conditions. The variables that had a strong correlation with the outcome were the depth of the water and the friction of the road, with correlation values of 0.657 and -0.635, respectively. However, since there is a limited number of car sensors and the RWIS is incapable of measuring these characteristics, we made the choice to exclude these three predictors. Relative humidity, which ranked fourth, had a correlation of 0.477 with the surface state. This indicates that there is a tendency for humidity to increase as road conditions get wetter, which is a sensible observation. Subsequently, the air temperature sensor, intake air temperature, ambient air temperature, and surface temperature were measured, yielding coefficients of -0.2968, -0.226, -0.2646, and -0.2774, respectively. The parameters that show low correlations, such as latitude and longitude, had a correlation coefficient of around -0.1. However, parameters such as barometric pressure and intake manifold pressure, which had correlations below 0.1, were considered to have no influence on the accuracy of the model and therefore were ignored. To summarize, the information chosen to be combined with the attributes of the picture consisted of ambient temperature and humidity.

4.2 Evaluation of RSC Based on Dashcam

4.2.1 Model Development and Comparison

To address the limited availability of frames in the partly and totally covered categories, we used oversampling techniques to expand the dataset. This resulted in a balanced distribution of 17,591 photos in three categories: 5,895 images of bare surfaces, 5,185 images of partially covered surfaces, and 6,511 images of fully covered surfaces. Building upon the research conducted by Juan[23], we implemented a convolutional neural network model for the purpose of feature extraction. For the transfer learning approach, we conducted three training sessions for each model, focusing on the fully connected layer (fc), the final 5% of the layers and the last 15%

of layers, respectively.

As previously mentioned, the models we select for transfer learning are: ResNet50[37], VGG16[38], Inception[39], and MobileNet[40]. During the training phase, the data sets were split into 90% for training and 10% for testing, with a learning rate of 0.001. Batch size and epoch count were set at 32 and 50, respectively, and pretrained ImageNet weights were used.

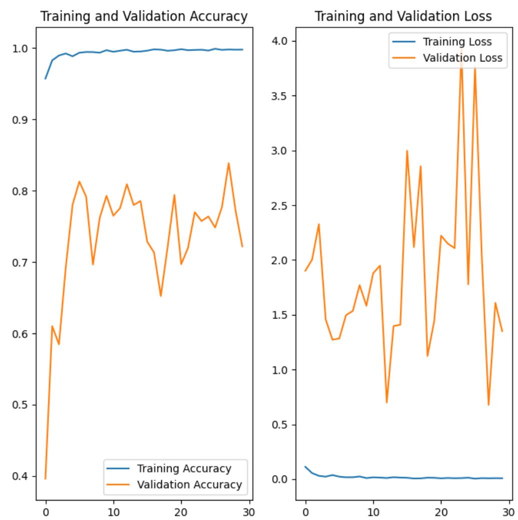


Figure 4.7: Accuracy and loss diagram for Resnet50

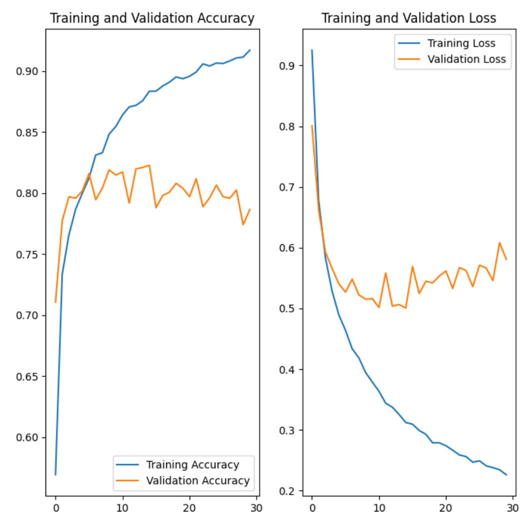


Figure 4.8: Accuracy and loss diagram for VGG16

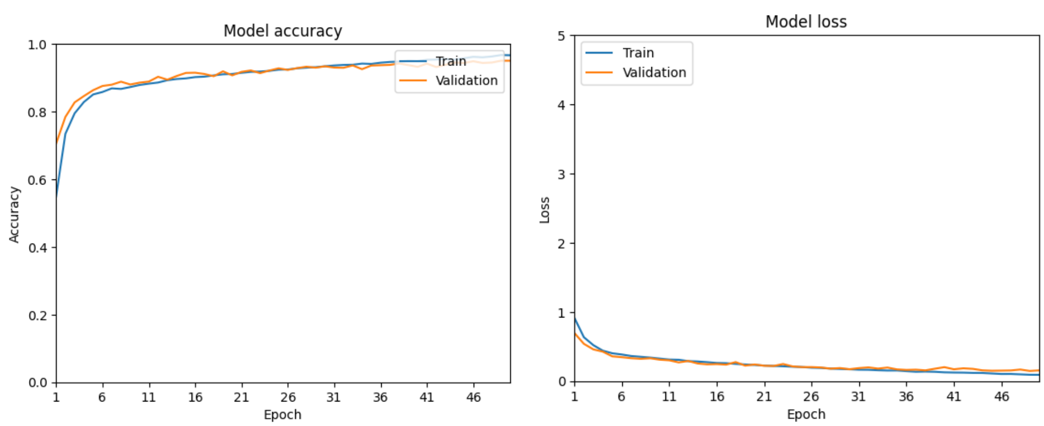


Figure 4.9: Accuracy and loss diagram for simple CNN

The performance of ResNet50 (4.7) and VGG16 (4.8), specifically on the fully connected layer, showed high accuracy and low loss on the training set but poor outcomes on the validation set, indicating weak generalizability and potential overfitting due to model complexity. On the contrary, simpler CNN models demonstrated robust performance, achieving 96% accuracy in both training and validation data sets after 50 epochs.

4.2.2 Factors Affecting Classification Model Accuracy

Testing model reliability in real-world conditions is essential. Drawing from prior research[41][42], we recognize that pure visual approaches can suffer accuracy fluctuations due to resolution and lighting variations. Consequently, this study explores the impact of different resolutions on our initial 224x224 setting and examines lighting effects on visual classification by altering image contrast.

The CNN model's performance is analyzed across several resolutions which shown in Table (4.1), and it achieves the highest accuracy of 97.1% at a resolution of 400x400. Remarkably, the accuracy reached its lowest point at a resolution of 600x600, namely at 96%. Based on the marginal variation of 1. 1% in accuracies, we may conclude that camera resolution has an insignificant effect on our straightforward three-category winter road surface condition classification problem.

Table 4.1: Accuracy and Loss of different input resolution

	Image Size			
Metric	224x224	300x300	400x400	600x600
Accuracy	96.23	96.39	97.1	96
Loss	0.1553	0.1543	0.1520	0.1559

However, unlike resolution, lighting greatly impacts classification accuracy. Initially, the model was trained with the original data set and then pre-processed to simulate low-light conditions by decreasing the exposure as shown in Figure (4.10).

The confusion matrix in Figure (4.11) revealed a significant decrease in accuracy from 96% to 49.5% by simply applying the model on the low-exposure dataset. Poor

Figure 4.10: decrease the image exposure to simulate bad lighting condition

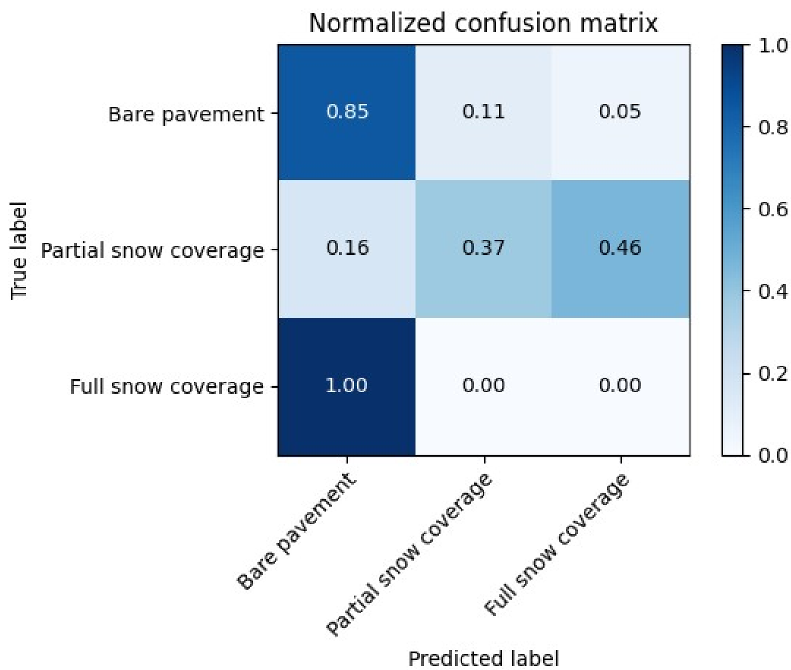


Figure 4.11: Confusion matrix when applying trained model on low-exposure dataset

performance was particularly observed in distinguishing between partial and full snow coverage, with most full snow coverage images misclassified as bare pavement. This misclassification may be due to reduced exposure making snow coverage resemble darker pavement, which aligns with our expectations.

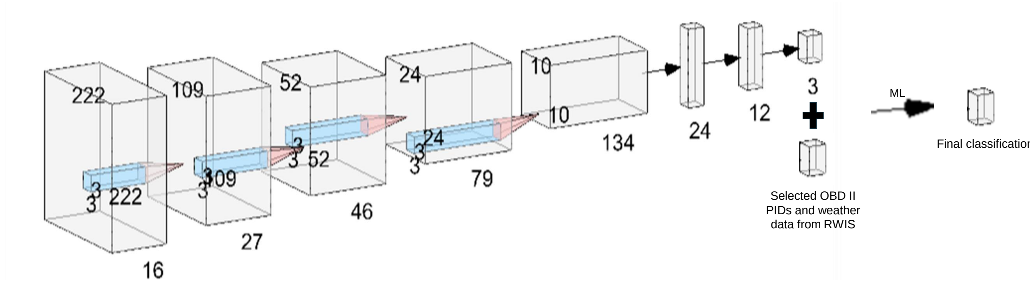


Figure 4.12: Integration process of vision data and weather data using CNN and machine learning

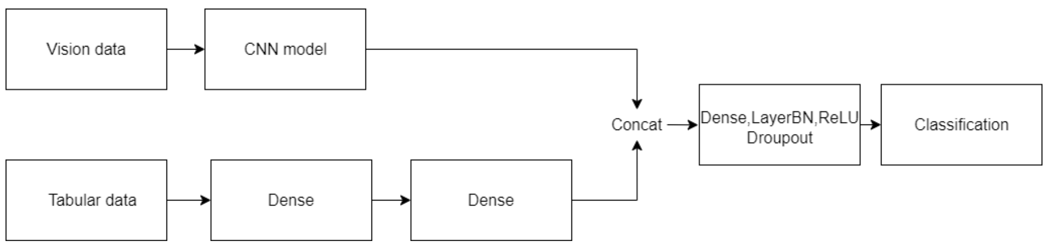


Figure 4.13: Integration process of vision data and weather data using CNN

4.3 Evaluation of RSC Based on Dashcam and the Weather Data Collected by Vehicle and RWIS Sensors

Although a simple CNN model may already achieved up to 96% accuracy during training and validation on the dataset, as discussed in the previous section, relying solely on the visual system may not ensure the reliability and stability of road prediction systems under complex real-life conditions. Drawing from prior research [23][10], we believe that integrating vision data (provided by the dashcam) and weather data collected by both vehicle sensors and RWIS stations is a viable approach to enhance the accuracy and reliability of road surface recognition.

We investigated two different data fusion strategies. One was proposed by Juan [10], with the specific process shown in Figure 4.12. The other was inspired by Nil's research [11], with the general architecture shown in Figure 4.13

Juan's method consists of two main parts. The first part involves feature extraction from vision data, resulting in a one-dimensional tensor for each image. The second part combines these one-dimensional tensors with selected weather data from vehicle sensors and RWIS stations. Machine learning techniques are then applied to the fused data to achieve the final classification of road conditions. In order to find the most suitable machine learning method, we tested Random Forest, Naive Bayes, and SVM classifiers. The performance of each classifier on the test dataset is summarized in Table (4.2). Among these classifiers, Random Forest demonstrated superior performance, making it our classifier of choice.

Nil's method also consists of two parts. The first branch extracts features from image data using a CNN. The image data input size is (224, 224, 3), and through a series of convolutional and max-pooling layers, the feature maps are gradually extracted and down sampled. Finally, global average pooling is applied to convert the convolutional feature maps into a one-dimensional vector, which is further processed by fully connected layers. The second part processes tabular data through multiple fully connected layers to extract features. The image and tabular data feature vectors are then concatenated, followed by further processing through a series of fully connected layers to produce the final classification output. For the image branch we adopted Juan's image feature extraction network as the baseline model and fine-tuned the channel and neuron parameters. The tabular data processing remained unchanged from the original study. During fine-tuning, the accuracy of each model on the test set is summarized in Table (4.3) . We found that when the number of channels was reduced to 0.5 times and the number of neurons increased to 1.5 times the baseline model, the overall model achieved the highest accuracy of 98.6% on the test set.

As shown in Figure 4.14, by plotting the confusion matrices for both methods, we noticed that Nil's method outperformed Juan's method in accurately classifying the 'snow fully covered' road class. Consequently, we chose Nil's architecture as the method for road surface state recognition in this study. Compared to using only visual data for road condition classification (Figure 4.15), the incorporation of visual data with supplementary modalities substantially improves the precision of the

Table 4.2: Performance Metrics of Different Machine Learning Classifiers

	Machine learning classifier		
Metric	Random Forest	Naive Bayes	SVM
accuracy	0.979	0.973	0.978
precision	0.9804	0.9730	0.98
Recall	0.9804	0.9730	0.98
F1 score	0.9804	0.9730	0.98

Table 4.3: Model fine tune for Nil's method

Metric	baseline	50% neuron	75% neuron	125% neuron	150% neuron
baseline	0.9771	NA	NA	NA	NA
50% channel	0.9804	0.953	0.9778	0.968	0.986
80% channel	0.973	NA	NA	NA	NA
120% channel	0.967	NA	NA	NA	NA
150% channel	0.976	NA	NA	NA	NA

model for the three categories assessed. This improvement is especially remarkable in the model's enhanced capacity to differentiate between 'uncovered road surface' and 'partially covered with snow'. The findings emphasize the effectiveness of data fusion in boosting the model's ability to distinguish and classify, underscoring the significance of using various data streams to enhance the accuracy of predictions in classification scenarios.

4.4 Performance Evaluation of the Selected Dynamic Segmentation Method

Given the limitations and challenges associated with real-world datasets on winter road surface conditions, including subjectivity in data labeling, noise due to limited sensor coverage area, and the lack of variability in some road segments, the decision

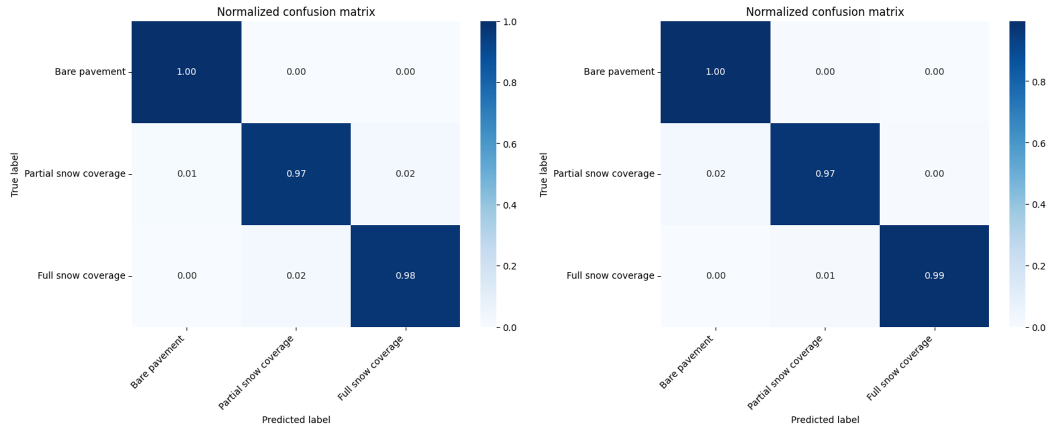


Figure 4.14: Left: Juan's fusion method; Right: Nil's fusion approach

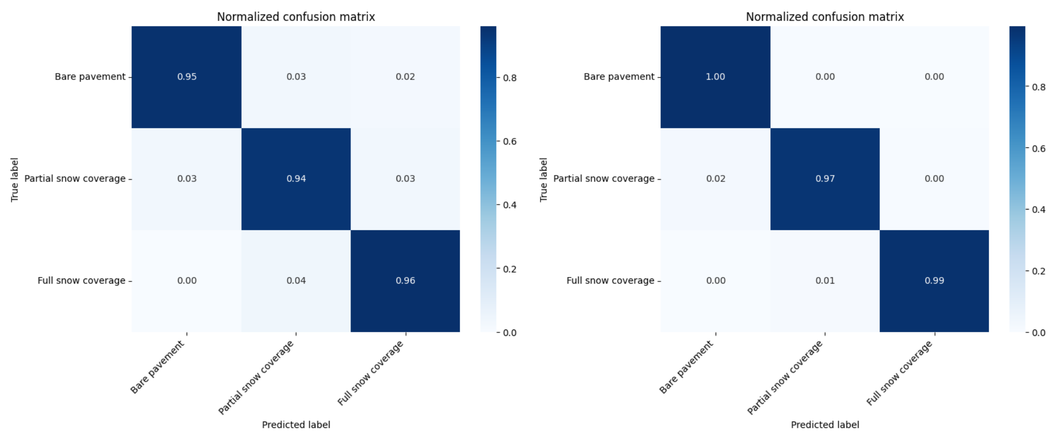


Figure 4.15: Left: Vision data as the only input; Right: Fuse the vision data and it's corresponding weather data

was made to use a synthetic dataset for this task. The synthetic dataset allows for a controlled environment where the characteristics of the data can be precisely defined and manipulated. This enables a more rigorous examination and comparison of dynamic segmentation techniques, and provides a clearer understanding of their strengths and weaknesses before applying them to real-world data.

4.4.1 Methods Comparison

Synthetic Dataset Development

The development of the synthetic dataset is guided by the Canadian government's classification of road surface conditions [43] which it divided into three categories:

bare, partially covered, or fully covered. Given that dynamic segmentation methods require numerical data, the initial step involves converting the textual data into numerical form. This conversion is facilitated by employing the RSI table[17], which serves as a reference to translate road condition descriptions into quantifiable metrics.

			Road surface index (RSI)		
Class	RSC category	RSC category defined by TAC	Max	Min	Average
1	Bare and Dry	Bare and Dry	0.9	1	0.95
2	Bare and Wet	Bare and Wet	0.8	0.9	0.85
3	Slushy	Partly Snow Packed, Partly Icy	0.7	0.8	0.75
4	Partly Snow Covered	Partly Snow Covered	0.5	0.7	0.6
5	Snow Covered	Snow Covered	0.3	0.5	0.4
6	Snow Packed	Snow Packed	0.2	0.3	0.25
7	Icy	Icy	0.05	0.2	0.125

Table 4.4: RSI Table

From the RSI table (4.4), we categorize road conditions into three classes with specific RSI ranges: 'Bare' (0.8 to 1), 'Partially Covered' (0.5 to 0.8), and 'Fully Covered' (0.05 to 0.5), taking average RSI values for each category as 0.9, 0.65, and 0.225 respectively. Considering a 200km corridor divided into 0.5km segments, we assume 9 segments with distinct RSI values varying from 0 to 1, ensuring adjacent segments have different RSIs. The noise in the data comprises normal random fluctuations and vehicle misjudgments of road conditions. Assuming an unbiased road condition estimator with uniformly distributed errors, there's a 2% chance of random misclassification into incorrect categories. This controlled introduction of noise allows for the testing of dynamic segmentation methods under conditions that closely mimic real-world challenges. The synthetic dataset, both with and without noise, is illustrated in Figure (4.16), which highlights the variations in RSI across the segments and the impact of noise on these measurements.

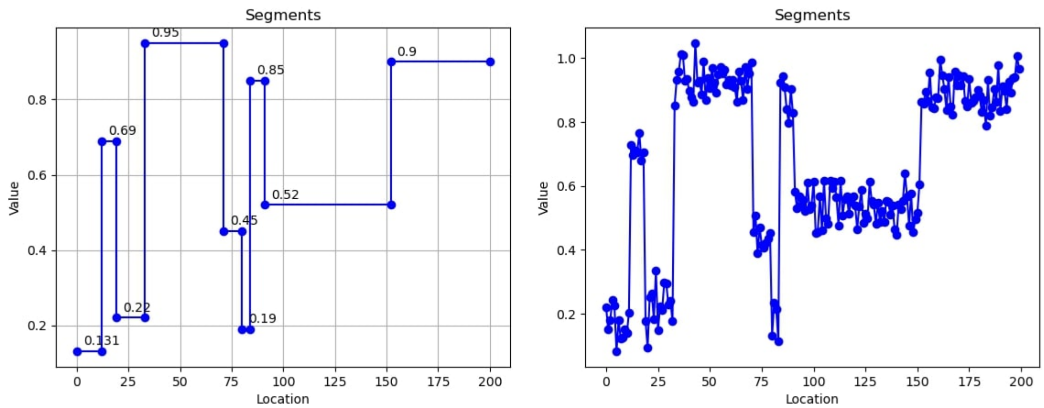


Figure 4.16: Left: Synthetic data without noise; Right: Synthetic data with noise

Comparison Between Different Segmentation Methods

In our study, we used 21 traditional changing-point-searching methodologies, along with two widely recognized techniques from the field of civil engineering: the CDA approach and a wavelet theory-based method. To facilitate a holistic evaluation of the performance of each method, we used four distinct metrics: precision and recall, Hausdorff distance, and Rand index. Ideally, both precision and recall, as well as the Rand index, should approach a value of 1 to indicate optimal performance, whereas a Hausdorff distance nearing 0 signifies more accurate segmentation. The accuracy of segmentation across the synthetic data, as assessed by these metrics for all the methods considered, is summarized in Table (4.5).

In the comparision presented in Table (4.5), the PELT technique, especially when using the Rbf cost model, demonstrates exceptional performance on several measures, achieving a Hausdorff distance of 0 and a Rand Index of 1. This emphasizes the efficiency of the PELT approach in reliably finding segmentation sites.

On the other hand, the Cumulative Distance Approach (CDA) demonstrates excellent performance without requiring an extra cost model. It achieves accuracy and recall rates of 1.0 and 0.875, respectively. Additionally, it has a Hausdorff distance of 3 and a Rand Index of 0.982663. The CDA approach showcases its ability to provide very precise segmentation results, even when a particular cost model is not available.

Table 4.5: Comparison of Segmentation Methods

Search Method	Cost Model	Precision	Recall	Hausdorff Distance	Rand Index
PELT	Rbf	0.875	0.875	0.0	1.0
PELT	Mahalanobis	0.875	0.875	0.0	1.0
PELT	L1	1.000	0.875	4.0	0.998
PELT	Rank	0.875	0.875	44.0	0.989
CDA approach	N/A	1.000	0.875	3.0	0.983
Wavelet approach	N/A	1.000	0.875	8.0	0.977
BinSeg	L2	0.571	1.000	43.0	0.954
Bottom Up	L2	0.571	1.000	43.0	0.954
Window Sliding	Normal	1.000	0.500	23.0	0.94
PELT	L2	1.000	0.375	21.0	0.915
Window Sliding	Mahalanobis	0.750	0.375	23.0	0.909
Window Sliding	AR	1.000	0.375	21.0	0.896
Window Sliding	Rbf	1.000	0.375	23.0	0.893
Window Sliding	L2	1.000	0.375	23.0	0.893
BinSeg	AR	0.348	1.000	43.0	0.862
Bottom Up	AR	0.308	1.000	43.0	0.856
BinSeg	Mahalanobis	0.296	1.000	43.0	0.851
BinSeg	L1	0.308	1.000	43.0	0.845
Bottom Up	Mahalanobis	0.276	1.000	43.0	0.837
Bottom Up	L1	0.276	1.000	43.0	0.833
BinSeg	Rank	0.250	1.000	43.0	0.832
Bottom Up	Rank	0.250	1.000	43.0	0.832
BinSeg	Rbf	0.250	1.000	43.0	0.831
Bottom Up	Rbf	0.250	1.000	43.0	0.831
BinSeg	Normal	0.205	1.000	43.0	0.821

The approach based on wavelet theory has somewhat poorer accuracy and recall, both measuring at 0.625. It also has a Hausdorff distance of 13 and a Rand Index of 0.948241. Although the wavelet technique does not achieve the same level of performance as the PELT or CDA approaches, it is nevertheless useful in some situations because of its ability to handle complicated data with noise or nonlinear characteristics.

Figure (4.17) shows the segmentation performance of the best-performing point-search technique, CDA, and the wavelet-based technique, respectively. The blue and red blocks represent the accurate representation of segmentation, whereas the dashed lines illustrate the results achieved by the segmentation techniques. The PELT+Rbf combo has the highest level of precision in determining segmentation borders. The Cumulative Distance approach fails to detect a segment within the range of 75-100 km, while the wavelet-based method exhibits suboptimal performance in the region of 75-125 km, where significant variations in road surface conditions exist. We believe that this difference might be because users have to fine-tune specific benchmark numbers based on how the data is structured. Segmentation quality may get worse if the changes aren't made correctly.

4.5 Application and Evaluation

To validate the proposed method and ensure that the data are not seen by the trained model, we independently collected data on Highway 2 in January 2024, with the route depicted in Figure (4.2). Since our test vehicle could not measure relative humidity, these data were provided by RWIS stations. For convenience, we selected RWIS stations within a 150 km radius of the midpoint of the route and performed ordinary Kriging interpolation to interpolate the regional relative humidity on that day. Through GPS coordinates, we obtained relative humidity values at each measurement point.

Subsequently, we converted the predicted RSC into the RSI and segmented it

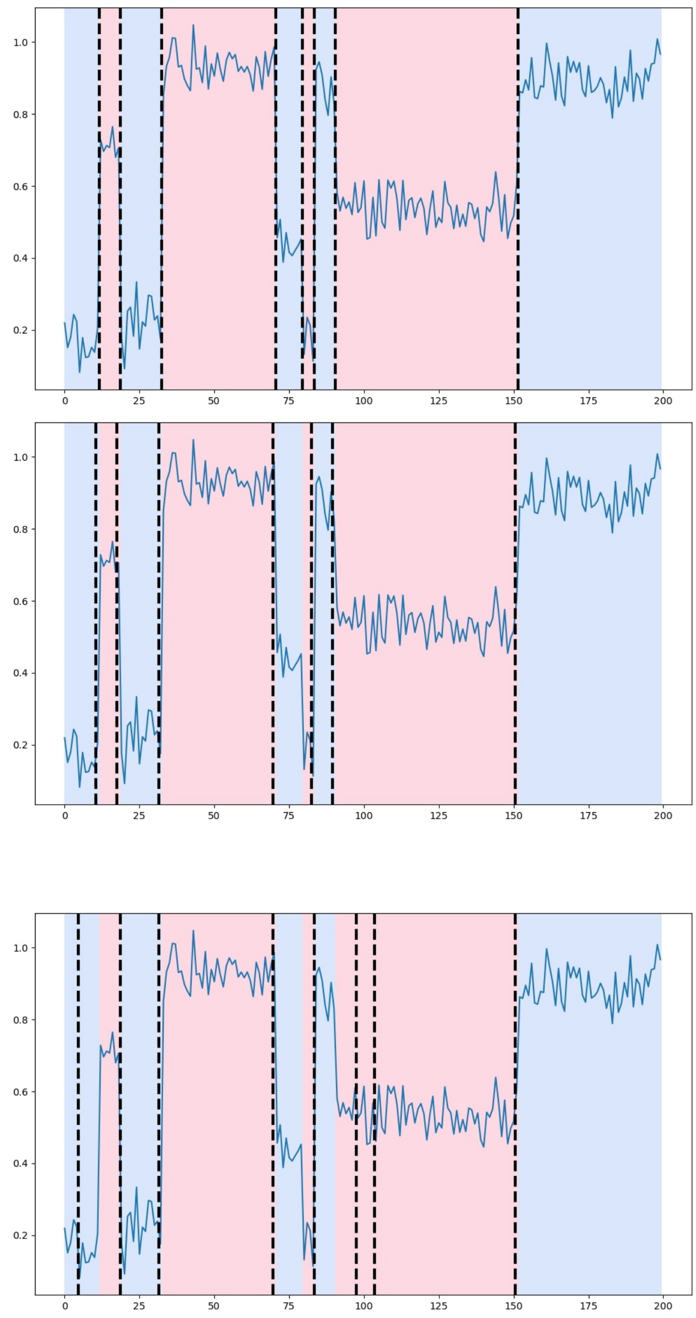


Figure 4.17: (a) Data segment by PELT-Rbf (b) Data segment by CDA (c) Data segment by wavelet-based method

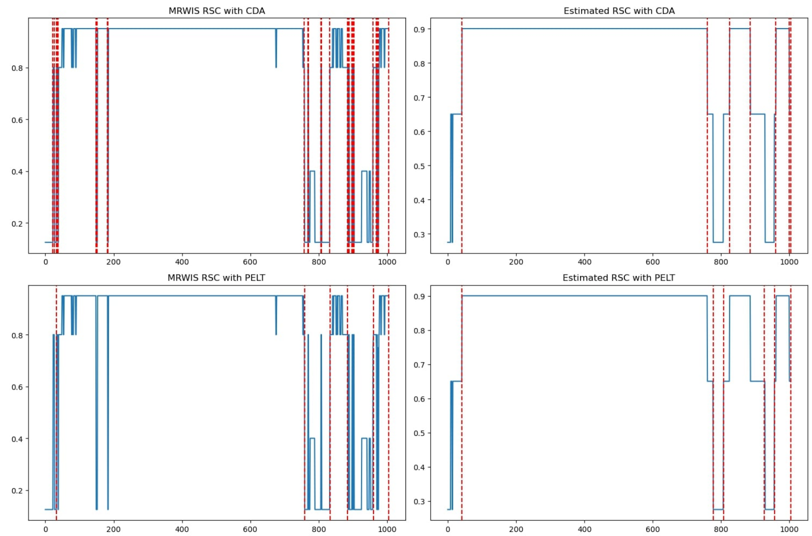


Figure 4.18: Road condition segmentation comparison between different methods and data sources

using the PELT-Rbf method as well as the widly used CDA method. We did the same procedure for the MRWIS data and treated it as our baseline.

When comparing the pattern of RSI shown in Figure (4.18), RSI measured by our approach is closely aligned with the results provided by MRWIS. This suggests that using dashcams and OBD can provide rather precise estimates of road conditions. The road condition patterns found in this experiment can be summarized as follows: The road conditions are primarily fully covered or partially covered from 0 to 50 measurement points. From 50 to 750 measurement points, the conditions are mostly bare. From 750 to 850, 850 to 900, 900 to 950, and 950 to 1000 measurement points, the road conditions alternate between being fully covered and bare. (Note: The reason for the symmetrical patterns noticed here is due to the vehicle's repetitive movement along the same road segment.)

In terms of road condition segmentation, the CDA technique exhibits a high level of sensitivity towards regions characterized by substantial fluctuations and noise in the data. Consequently, this sensitivity results in the generation of several segments that are either too close to each other or superfluous. This is particularly evident in the vicinity of the 200 and 900 measurement points. Nevertheless, the PELT approach does not encounter this problem when used with an identical dataset.

In terms of RSI prediction, our system that combines dashcam, onboard diagnostics (OBD), and Road Weather Information System (RWIS) falls short in terms of providing the same level of detail as the MRWIS data. The main reason for this is the classification of the training set into only three categories. Increasing the number of categories may improve the outcomes, however, it could also result in a reduction in the accuracy of identifying road conditions.

We assume MRWIS + CDA as the baseline for comparison. The following table, referenced as Table (4.6), presents the evaluation metrics obtained by comparing various segmentation approaches against this baseline.

Table 4.6: Comparison of Precision and Recall for Different Data Sources and The Selected Dynamic Segmentation Methods

	MRWIS+CDA	
	Precision	Recall
MRWIS+CDA	1	1
Estimated+CDA	0.857	0.286
MRWIS+PELT	1	0.286
Estimated+PELT	0.833	0.238

When comparing different methods for estimating RSC, it has been found that using a combination of dashcam, OBD, and RWIS data results in higher precision but lower recall rates when segmenting with the CDA or PELT method compared to the benchmark MRWIS+CDA approach. This difference arises because MRWIS data, which only measures real-time road conditions under the left rear wheel, can sometimes misrepresent the overall road condition. This misrepresentation introduces noise that affects segmentation performance, leading to more segmentation points. Consequently, the hybrid technique, while providing a broader perspective and avoiding such noise, results in fewer segmentation points.

Although MRWIS data has been proven to be a reliable source for measuring road surface conditions, the high costs associated with manual labor and equipment make it impractical for widespread use. Consequently, road surface conditions are often estimated using stationary RWIS data and contractor reports in practical scenarios. These methods do not achieve the same level of accuracy or real-time capability to predict road surface conditions as MRWIS or the hybrid method that combines dashcam, OBD and RWIS data.

4.6 Summary

In this chapter, a comprehensive case study was conducted to evaluate road surface conditions (RSC) during winter on Highway 2, south of Edmonton, Alberta. The region's high latitude and significant snowfall made it an ideal location to collect detailed road surface data. The study used a combination of a mobile Road Weather Information System (RWIS), a dashcam, an OBD-USB adapter, and data from the 511alberta API.

The data collection took place during the winter of 2022-2023, with four sessions capturing various road conditions from dry to fully covered with snow. Initially, video frames from the dashcam were classified into three categories: bare/dry, partially covered snow, and fully covered snow. Despite high training and validation accuracy, the image-level labeling approach resulted in severe overfitting, indicating the need for cropping images to focus on road conditions.

Data analysis revealed strong correlations between certain vehicle and RWIS sensor data and road surface conditions, particularly relative humidity and temperature. A substantial dataset of 10,728 synced data items was collected, with categorical data transformed into numerical values for analysis.

Various convolutional neural network (CNN) models were tested, with simpler models demonstrating better generalizability compared to more complex ones. Factors such as resolution and lighting significantly impacted model performance, with lighting conditions causing substantial accuracy drops.

To improve overall accuracy and reliability, vision data was integrated with weather data from vehicle sensors and RWIS stations. This data fusion approach resulted in an approximate 2% improvement in accuracy. Among the classifiers tested, Random Forest demonstrated superior performance, making it the classifier of choice for the integrated data.

Due to the lack of comprehensive real-world data, a synthetic dataset was developed to test dynamic segmentation methods. The study found that the PELT method with the Rbf cost model and the Cumulative Distance Approach (CDA) showed the best performance in segmenting road conditions.

An independent data collection in January 2024 validated the proposed methods. The hybrid approach, which combined dashcam, OBD and RWIS data, aligned well with MRWIS data, demonstrating the effectiveness of using multiple data sources. The PELT method provided more reliable segmentation results compared to the CDA method, which was sensitive to data noise and fluctuations.

In conclusion, this case study highlighted the importance of integrating various data streams to enhance the accuracy of winter road surface condition assessments. The findings underscore the effectiveness of advanced segmentation techniques and the need for more research to improve the classification accuracy of image data and address challenges such as lighting variations and data noise.

Chapter 5

Conclusions, Recommendations, & Future Work

5.1 Conclusions

In this research, we aimed to predict Road Surface Conditions (RSC) in real-time on the vehicle side by combining onboard cameras, vehicle sensors and data from RWIS stations. We evaluated various image recognition and fusion methods and selected the one that provided high accuracy in predictions. For dynamic segmentation, we experimented with two commonly used dynamic segmentation methods in civil engineering and several standard change point detection techniques. Our comparison on synthetic data showed that the PELT-Rbf method had better segmentation accuracy. We also conducted a case study with data collected specifically on Highway 2, demonstrating that our method could effectively predict and segment the states of the winter road surface in real-life scenario.

5.2 Recommendations and Future Work

Future research efforts could be directed towards several key areas to enhance RSC estimation and segmentation technologies. A primary area of focus might be the development of methodologies for the precise labeling of image datasets captured by dashcams, ensuring the accuracy of the labels and determining the ideal balance between the number of classes and the overall accuracy of the segmentation model.

In addition, optimizing vehicle sampling rate is essential to effectively balancing cost and performance. By adjusting the frequency at which data is collected from vehicles, researchers can reduce the costs associated with data processing and storage, while still maintaining a dataset that is robust enough for accurate analysis.

Data preprocessing is another critical area for improvement. Techniques such as applying greyscale or picture-enhancing methods to increase contrast and highlight additional details could lead to more effective segmentation by emphasizing key features within the imagery. Moreover, considering the influence of lighting conditions and road surface material colors, datasets could be further classified based on factors such as day and night conditions and the type of road surface material. This additional classification step may significantly improve the model's reliability in real-world applications, ensuring more accurate predictions across varying environments.

Significant advancements are also needed in road surface segmentation technologies. For example, integrating actual road maintenance costs into segmentation models could yield a more comprehensive understanding of the implications of road conditions. Furthermore, lane-specific RSC detection could provide more detailed information on road surface conditions, which is critical for targeted maintenance and improving road safety.

Leveraging deep learning techniques could also revolutionize the refinement of dynamic segmentation parameters, increasing the adaptability and performance of segmentation models across a variety of datasets. Additionally, exploring advanced data fusion techniques, such as multihead cross-attention mechanisms, may improve the integration of disparate data sources, thereby enhancing predictive accuracy. Such integration could lead to a more nuanced and holistic analysis of road surface conditions by effectively combining information from different sensors and data modalities.

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